

# Space-Time Crop & Attend: Improving Cross-modal Video Representation Learning.

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## Abstract

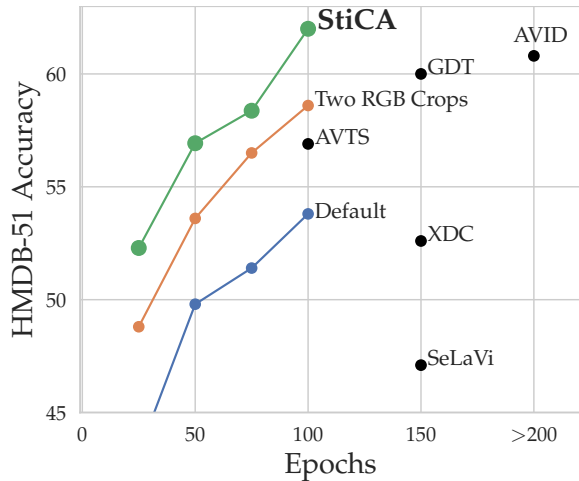
The quality of the image representations obtained from self-supervised learning depends strongly on the type of data augmentations used in the learning formulation. Recent papers have ported these methods from still images to videos and found that leveraging both audio and video signals yields strong gains; however, they did not find that spatial augmentations such as cropping, which are very important for still images, work as well for videos. In this paper, we improve these formulations in two ways unique to the spatio-temporal aspect of videos. First, for space, we show that spatial augmentations such as cropping do work well for videos too, but that previous implementations, due to the high processing and memory cost, could not do this at a scale sufficient for it to work well. To address this issue, we first introduce *Feature Crop*, a method to simulate such augmentations much more efficiently directly in feature space. Second, we show that as opposed to naïve average pooling, the use of transformer-based attention improves performance significantly, and is well suited for processing feature crops. Combining both of our discoveries into a new method, *Space-Time Crop & Attend (STiCA)* we achieve state-of-the-art performance across multiple video-representation learning benchmarks. In particular, we achieve new state-of-the-art accuracies of 67.0% on HMDB-51 and 93.1% on UCF-101 when pre-training on Kinetics-400. Code and pretrained models are available<sup>1</sup>.

## 1. Introduction

Visual representations have evolved significantly in the last two decades. The first generation of representations

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<sup>1</sup><https://github.com/facebookresearch/GDT>



**Figure 1: HMDB-51 accuracy vs epoch.** Our method, **STiCA**, combines space-time crops in feature space with self-attention of time in latent space. This yields significant benefits not only in performance but also in speed compared to cropping in input space using *two RGB crops*, or simply using the *default* cross-modal only loss. Compared to recent state-of-the-art cross-modal self-supervised learning methods (XDC [6], GDT [106], AVID-CMA [97], SeLaVi [9]) pre-trained on Kinetics-400 [69] STiCA is able to achieve significantly better results in fewer epochs.

comprises algorithms such as SIFT [87] and HOG [30] that were designed manually. The second generation comprises representations learned from data by using deep neural networks and manual supervision [31, 59, 76]. We are now transitioning to the third generation, where representations are learned from data without using any manual annotations by means of self-supervision. Current self-supervised rep-

representations, obtained from methods such as MoCo [57], SimCLR [24] or SwAV [20], convincingly outperform supervised ones on downstream tasks such as image classification, segmentation and object detection. Furthermore, most of these methods are based on noise-contrastive instance discrimination, which was proposed in ExemplarCNNs [39] and put in its current form in [142] and [101]. The idea is to learn representations that are invariant to irrelevant factors of variations, modelled by strong augmentations such as image cropping, while remaining distinctive for the identity of the image.

Noise-contrastive learning is of course not limited to still images. In particular, a number of recent approaches [54, 93, 97, 106] have used noise-contrastive formulations to learn visual or audio-visual representations. However, these methods are not as well developed as their counterparts for still images, with current state-of-the-art methods [54, 106] still lagging behind their supervised counterparts.

In this paper, we identify two areas in which current video representation learning formulations are lacking and improve on them, thus significantly improving upon the current state of the art in this area.

The first shortcoming is the lack of a sufficient encoding of **spatial invariances**. For still images, learning spatial invariances has been shown to be one of the most important factors for performance [20, 24]. Almost all methods achieve some form of spatial invariance simply by applying different spatial augmentations to the images in different epochs of training. However, learning spatial invariances in this manner requires a slow training process that lasts for many epochs ( $\sim 800$ ). Authors have suggested that packing several augmentations of the same image in a single data batch is more effective as it provides a much stronger and more direct incentive for the network to learn invariances [20].

For videos, both strategies are less feasible. Training a model for 200 epochs on Kinetics-400 [69] already requires around 1.5K GPU hours on recent Nvidia V100 architectures, and with recent datasets such as IG65M [45] and HowTo100M [94] only a handful of epochs can realistically be completed. On the other hand, including multiple augmentations of the same video in a batch rapidly exhausts the memory of GPUs. Since batch sizes per GPU are already in the single digits due to the size of video data, including several augmentations is unfeasible. This is particularly detrimental for recent contrastive learning approaches such as [24, 58], where reducing the batch size means reducing the pool of negative contrastive samples.

In order to solve this problem, we propose to move spatial augmentations to the feature space, in a manner specifically tailored to contrastive learning. Instead of extracting a large number  $R$  of different augmentations in the input RGB space, we extract only two of them, apply the trunk of the

neural network to extract corresponding features, and then extract  $R/2$  more augmentations directly in feature space. In this way, one needs to evaluate the slow and memory taxing feature extraction part of the network only twice, regardless of the number of augmentations that are produced. We show that this *feature-level augmentation* significantly improves representation learning performance.

The second challenge that we tackle is how to best encode **temporal information** in self-supervised video representation learning. Currently, most self-supervised video representation learning approaches use 3D-CNNs [21, 132, 133, 144] that compute convolutions across space and time, but the final representation is generated by naïve global average pooling over space and time, crucially discarding temporal ordering.

In order to address this shortcoming, in this work we propose to use a contextualized pooling function based on the transformer architecture [135] for both self-supervised pretraining and supervised finetuning. The intuition is that, via multi-head self-attention, the transformer can capture temporal dependencies much better than average pooling, especially for longer inputs. Transformers can also benefit from our feature-level crops, as the latter resemble the common approach of randomly masking the inputs to the transformer [62]. Experimental results show that this modification improves the performance of the learned video representations substantially, and is cumulative with the benefit of feature crops, at about the same cost of average pooling.

We combine both of our proposed improvements into a new self-supervised learning approach: Space-Time Attention and Cropping (**STiCA**). To summarize, with STiCA we make the following three main contributions:

- We demonstrate the benefits of stronger spatial invariances in self-supervised video representation learning for the first time and we propose feature-level augmentation to implement the latter efficiently.
- We propose to use transformers to model time more effectively in self-supervised video representations, replacing average as the pooling function.
- We demonstrate strong performance gains by using the two techniques and obtain state-of-the-art performance on two standard benchmarks (67.0% on HMDB-51 and 93.1% on UCF-101).

## 2. Related Works

**Self-supervised Image Representation Learning.** Self-supervised learning uses pretext tasks to automatically and easily generate differentiable learning signals from the data itself in order to train convolutional neural networks. A variety of pretext tasks have been proposed such as colorization [148, 149], predicting artificial rotations [46], in-

painting [105], spatial context [35, 100], and clustering features [11, 18, 19, 20, 64, 83]. Recently, contrastive methods [50, 51] have proven to be particularly effective at learning transferable image representations [13, 24, 49, 57, 95, 101, 130].

**Self-supervised Video Representation Learning.** For videos, pretext tasks often seek to leverage the temporal dimension to learn representations. Such tasks include predicting clip and sequence order [79, 96, 145], future events [52, 53], the arrow of time [140], 3D geometric transformations [65, 71], playback speed [14, 40, 63, 137], or motion statistics [136].

**Multi-Modal Learning.** The co-occurrence and synchronicity of multiple modalities from videos have been used to learn visual representations from both audio-video [6, 7, 9, 74, 90, 97, 102, 106], and speech-video [5, 73, 85, 92, 93, 98, 107, 123, 125, 126] data. Multi-modal representation learning has several practical applications: lip reading [3, 26, 27], audio-visual source separation and localization [2, 4, 8, 56, 150, 151], speech recognition [1, 111], efficient inference [43, 75], egocentric action recognition [70] and audio-visual navigation [22].

**Data Augmentations.** Data augmentation has proven to be useful in training deep learning models in many domains, from vision [28, 29, 146] to speech [103]. Data transformations are the foundation of most self-supervised works, and there has been early attempts to even learn the optimal distribution of transformations [16, 29]. Particularly for contrastive learning, the choice of data transformations has been shown to be particularly important to learn desirable invariances and equivariances [95, 106, 130, 131].

**Transformations in Feature-Space.** Some works have proposed forms of augmentation in feature-space, by adding noise and linear transformations [129], and by associating samples to prototypes in feature-space [78]. These augmentations do not correspond to interpretable geometric operations, however. Crops in feature-space are commonly used in supervised detection pipelines, such as Faster R-CNN and region-based architectures [115], and in earlier detectors based on manually-engineered features [30]. However, the objective of these transformations is to enumerate a space of outputs (e.g. bounding box predictions) for supervised prediction. In self-supervised learning, while [66] uses feature mixing to create harder negatives for contrastive learning, we are instead interested in using feature crop augmentation to achieve spatial invariance.

**Temporal Modeling.** Videos extend images by adding a temporal dimension. Therefore, there has been a large family of research that has looked into how to model temporal information in videos. Early works incorporated temporal information via average pooling of frame/clip-level

features [48, 68, 138], while later work used 3D convolutional neural networks [132, 133, 144] and recurrent-neural networks [37]. Other approaches leverage long-term temporal convolutions [134], self-attention [139], relation networks [152], multi-scale temporal convolutions [61], or optical flow in a two stream network [119].

**Transformers in Vision.** With the success of the transformer architecture [135] in natural language processing [62], transformers are being used in various vision domains such as image representation learning [23, 32, 38, 118, 141], image generation [104], object detection [17, 86], few-shot learning [36], video action recognition [15, 47, 99, 139], video question-answering [67], image-text [84, 88, 124, 127, 128] and video-text [42, 73, 107, 125, 126, 154] representation learning.

### 3. Method

Our goal is to learn a general-purpose *data representation*  $\Phi : \mathcal{X} \rightarrow \mathcal{Z} = \mathbb{R}^D$  that maps data  $x \in \mathcal{X}$  to feature vectors  $z = \Phi(x)$ . In the supervised setting, representations are learned end-to-end as components of larger systems that solve certain tasks of interest, such as image or video classification, under the assumption that supervision is available to drive the learning process. When supervision is not available, representations can still be learned via self-supervision by means of suitable pretext tasks. Among the latter, *noise contrastive learning* is one of the most popular and successful ones [24, 101]. We summarize this background next and discuss our extensions in the following sections.

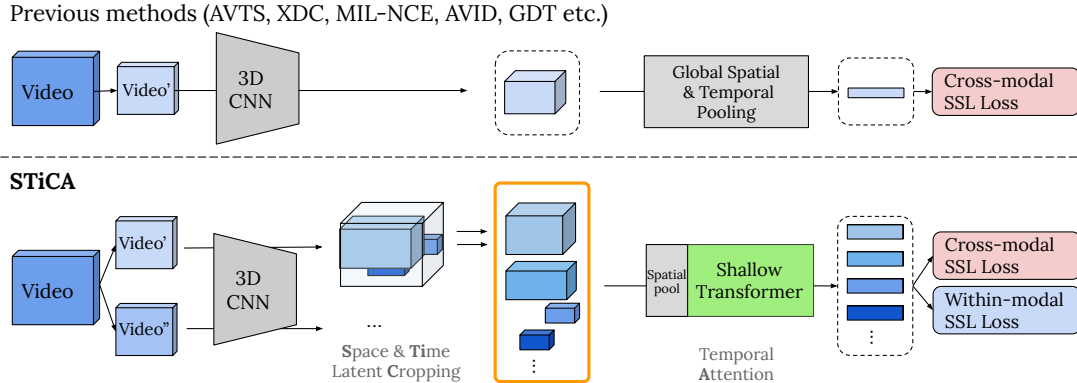
#### 3.1. Background: Multi-modal contrastive learning

The idea is to train the representation  $\Phi$  to identify data points up to the addition of noise or, more generally, the application of certain nuisance transformations. To this end, let  $g : \mathcal{X} \rightarrow \mathcal{X}$  be transformations sampled in a set  $\mathcal{G}$  of possible nuisances (for example random image crops). Let  $\text{sim}(z', z'')$  be a similarity function comparing representations  $z'$  and  $z''$ , such as the cosine similarity:

$$\text{sim}(z', z'') = \frac{\langle z', z'' \rangle}{\|z'\| \|z''\|}.$$

Consider a dataset or batch  $\mathcal{B} = \{x_1, \dots, x_N\}$  of data samples. Slightly modifying [24], for each sample  $x_i$ , draw a set of random nuisance transformations  $\{g_{\alpha i}\}_{1 \leq i \leq N}$  and let  $z_{\alpha i} = \Phi(g_{\alpha i}(x_i))$  be the representations of the transformed samples. Likewise, consider a second set  $\beta$  of transformations  $\{g_{\beta i}\}_{1 \leq i \leq N}$ . The noise contrastive loss (NCE) is given by:

$$\mathcal{L}(\alpha, \beta) = -\frac{1}{N} \sum_{i=1}^N \log \frac{e^{\frac{1}{\tau} \text{sim}(z_{\alpha i}, z_{\beta i})}}{\sum_{j=1}^N e^{\frac{1}{\tau} \text{sim}(z_{\alpha i}, z_{\beta j})}} \quad (1)$$



**Figure 2: Approach Overview.** We present a self-supervised approach that learns video representations without labels. **(Top)** Prior work in video representation learning did not capture spatial invariances, as taking many crops of the input (at varying locations and scales), quickly gets expensive in both compute and memory. **(Bottom)** The proposed method generates a large variety of views from only two RGB-crops by cropping in latent space and is particularly tailored to self-supervised contrastive learning. The latent crops are essentially masked features, which are then further processed by a light-weight temporal transformer. Compared to global pooling, this allows our method to further capture the rich temporal signal.

where  $\tau > 0$  is a temperature parameter. This loss pulls together the representations of samples that only differ by the transformation while pushing apart the others. Note that this definition is not symmetric in the two arguments  $\alpha$  and  $\beta$  (i.e.,  $\mathcal{L}(\alpha, \beta) \neq \mathcal{L}(\beta, \alpha)$ ). Note also that we can introduce any number of transformation sets  $\alpha, \beta, \gamma, \dots$  and, for each pair, we can obtain a different variant of eq. (1).

Recently, works such as [106] have ported this technique to the video domain by contrasting modalities. Each video  $\mathbf{x} = (v, a)$  consists of a visual component  $v$  and an audio component  $a$ . One consider two sets of transformations  $g_v$ , extracting and augmenting the visual component, and  $g_a$ , extracting and augmenting the audio component. We still write  $\Phi(g_\alpha(\mathbf{x}))$  for the feature computed for either visual and audio components, but the symbol means that a modality-specific neural network is applied as needed.<sup>2</sup>

With this, we can derive three variants of eq. (1), involving mixed visual-audio and homogeneous visual-visual and audio-audio comparisons. Their combinations are:

$$\lambda_{va}\mathcal{L}(v, a) + \lambda_{av}\mathcal{L}(a, v) + \lambda_{vv}\mathcal{L}(v_1, v_2) + \lambda_{aa}\mathcal{L}(a_1, a_2). \quad (2)$$

where  $\lambda_{va}$ ,  $\lambda_{av}$ ,  $\lambda_{vv}$  and  $\lambda_{aa}$  are non-negative mixing weights.

### Challenge 1: Encoding within-modality invariance.

While all terms in 2 code for desirable invariances of the representation, several recent papers [90, 97, 106] have found that the mixed term  $\lambda_{va}$  is far more important than the other two; in fact, performance *degrades* if one sets  $\lambda_{aa}, \lambda_{vv} \neq 0$ , meaning that within-modal invariances are

<sup>2</sup>In other words,  $\Phi = (\Phi_v, \Phi_a)$  is really a pair of networks, producing embedding vectors  $\mathbf{z}_\alpha$  that are compatible regardless of the modality  $\alpha \in \{v, a\}$ .

not successfully leveraged. Our hypothesis is that within-modality invariance can be beneficial, and that these early negative results are due to the fact that current learning formulations are ineffective at capitalizing on this signal.

As suggested in Sec. 1, the fact that video data is large means that the batch size used in learning must be small. As a consequence, a batch can contain only a very small number of different augmentations of the same video sample. In current multi-modal learning formulations, each video is already transformed twice in order to extract video and audio components, so cross-modal invariance is learned well. However, the downside is that there is no space left in the batch for multiple visual or audio augmentations. Thus, within-modality invariance is learned only indirectly — in particular, as noted in Sec. 1, two different visual or audio augmentations of the same video are visited by the model only after an entire training epoch. Next, we address this issue by making it feasible to extract several within-modality transformations in the same batch even for video data.

### 3.2. Efficient spatial cropping for augmentation

It has been found that self-supervised learning benefits from, and requires more and stronger augmentations compared to the supervised counterpart for optimal performance [24]. In particular, several papers [10, 20, 24] have suggested that, in the case of still images, the most important type of augmentation is *cropping*. Namely, given an RGB image  $\mathbf{x} \in \mathbb{R}^{3 \times H \times W}$  with three channels and height and width  $H$  and  $W$  respectively, a crop is given by a box  $B = (x_{\min}, x_{\max}, y_{\min}, y_{\max})$ . The image tensor is first cropped as:

$$C_B(\mathbf{x}) = \mathbf{x}_{[:, y_{\min}:y_{\max}, x_{\min}:x_{\max}]} \quad (3)$$

where the  $:$  symbol is used to denote an index range. The cropped tensor is then resized to a tensor  $\tilde{\mathbf{x}} = g(\mathbf{x}) = R_{H_0 W_0}(C_B(\mathbf{x})) \in \mathbb{R}^{3 \times H_0 \times W_0}$  with a given height and width  $H_0 \times W_0$ . In practice,  $R_{H_0 W_0}$  may also apply additional augmentations such as color jittering, as detailed in the experiments.

As for the visual part  $\mathbf{v} \in \mathbb{R}^{3 \times T \times H \times W}$  of a video, the situation is similar, except that the video also contains an additional temporal dimension  $T$ . To avoid extreme spatial jittering and keep objects aligned, a spatial crop is usually taken at the same location in the input space throughout the whole temporal dimension, so we consider the tube  $B = (x_{\min}, x_{\max}, y_{\min}, y_{\max}, t_{\min}, t_{\max})$  and define  $\tilde{\mathbf{v}} = g_v(\mathbf{v}) = R_{H_0 W_0}(C_B(\mathbf{v})) \in \mathbb{R}^{3 \times T_0 \times H_0 \times W_0}$  by extending (3) in the obvious way.

The deep neural network  $\mathbf{z} = \Phi(\tilde{\mathbf{v}})$  mapping  $\mathbf{v}$  to its corresponding code  $\mathbf{z}$  is fed with tensors with two spatial dimensions and a temporal one. Such networks, often called 3D for this reason, include R3D [55], S3D [144] and R(2+1)D [133]. As customary in deep convolutional neural networks, they first produce an intermediate tensor with lower space-time resolution and then pool the latter to obtain a single code vector for the entire video. We explicitly break this down into three functions

$$\Phi(\tilde{\mathbf{v}}) = (\mathcal{P}_t \circ \mathcal{P}_s \circ \Psi)(\tilde{\mathbf{v}}) \quad (4)$$

Here, the first function is a 3D convolutional neural network  $\Psi(\tilde{\mathbf{v}}) \in \mathbb{R}^{D \times T_1 \times H_1 \times W_1}$  producing a tensor with reduced resolution  $T_1 < T_0$ ,  $H_1 < H_0$ ,  $W_1 < W_0$ . The operators  $\mathcal{P}_s$  and  $\mathcal{P}_t$  collapse, respectively, spatial and time dimensions via average pooling.

Now consider implementing term  $\mathcal{L}(v_1, v_2)$  in 2. In this case, one samples from each video  $\mathbf{x}_i$  two different space-time crops  $g_{v_1 i}(\mathbf{x}_i)$  and  $g_{v_2 i}(\mathbf{x}_i)$ , each corresponding to random tubes  $B_1$  and  $B_2$  respectively. The tubes are not sampled entirely independently, however, as they have the same temporal extent  $(t_{\min}, t_{\max})$ .

**Naïve multiple spatial cropping** In practice, [20, 24, 82, 95] show that taking multiple image crops improves self-supervised image representations. We can achieve a similar effect for videos by summing losses  $\mathcal{L}(v_\alpha, v_\beta)$  for sets of visual transformations  $v_\alpha \neq v_\beta$ , obtained by sampling multiple space-time tubes for each video, but this is practically difficult, both due to the large memory footprint and the compute overhead of the slow 3D CNN for each crop.

The Multi-Crop approach introduced by SwAV [20] in the image domain combined with our asymmetric contrastive formulation (1) can partially reduce the complexity. For Multi-Crop, we consider three crop sizes  $\alpha \in \{L_1, L_2, S\}$  where  $L_1$  and  $L_2$  stands for large and  $S$  for small. The use of a small crop allows to reduce the memory consumption when the representation  $\Phi$  is computed. We

then have losses:

$$\mathcal{L}(v_{L_1}, v_{L_2}) + \mathcal{L}(v_{L_2}, v_{L_1}) + \mathcal{L}(v_{L_1}, v_S) + \mathcal{L}(v_{L_2}, v_S).$$

While operating on small videos saves some computation, in practice this approach is insufficient to allow using more than a handful of crops in total.

**Efficient cropping in feature space.** As illustrated in Fig. 2, a much more efficient alternative to cropping the input video is to crop intermediate features.

To do so, we first apply the trunk  $\Psi$  of the representation to an input-space crop of the visual component of the video  $\tilde{\mathbf{v}} = R_{H_0 W_0}(C_B(\mathbf{v})) \in \mathbb{R}^{D \times T_1 \times H_1 \times W_1}$ . Then we can efficiently construct a new view of this data by applying the *Feature Crop*  $C_{\tilde{B}}$  directly on each intermediate representation, yielding

$$\tilde{\mathbf{v}} = C_{\tilde{B}}(\Psi(\tilde{\mathbf{v}})) = \Psi(\tilde{\mathbf{v}})_{[t_{\min}:t_{\max}, y_{\min}:y_{\max}, x_{\min}:x_{\max}]} \quad (5)$$

Since the operator  $C_{\tilde{B}}$  is lightweight, it can be used to compute several such random views efficiently; by comparison, cropping the input RGB images requires recomputing the trunk  $\Psi$  multiple times.

In practice, given an input video  $\mathbf{v}$ , we generate the following views. First, we apply two crops in RGB space, producing two large crops  $L_1$  and  $L_2$ . Then, for each of those, we use the operator (5) to generate  $m$  medium-sized and  $n$  small-sized crops  $\mathcal{T}_i = \{M_1 L_i, \dots, M_m L_i, S_1 L_i, \dots, S_n L_i\}$ . We define an overall within-modality loss by summing losses for each pairs of views in  $\mathcal{T}$  with exception of pairs where both crops are small:

$$L_{vv} = \sum_{\alpha, \beta} \mathcal{L}(v_\alpha, v_\beta) + \mathcal{L}(v_\beta, v_\alpha), \quad \text{where} \\ (\alpha, \beta) \in (\mathcal{T}_1 \times \mathcal{T}_2) - (\mathcal{S}_1 \times \mathcal{S}_2) \quad (6)$$

Note that there are  $2((m+n)^2 - n^2)$  terms in this loss. This is a far greater number of comparison than afforded by the two initial input-space RGB crops.

### 3.3. Temporal modelling with transformers

We now discuss our second improvement: better modelling of time.

**Challenge 2: Modelling time better.** Contrary to spatial invariance, models should not be fully invariant to time as the latter can encode causality and with it semantics: a video of someone starting a fire is very different from its reversed version, in which someone extinguishes it. In standard 3D networks, features in the trunk are sensitive to the temporal order, but this information is lost in the final stage, where temporal averaging is applied. We argue that the value of the lost information increases with the length of the video, and that this information can be leveraged by switching to a different pooling function.



**Temporal transformer.** We propose to tackle this issue by replacing average pooling in time  $\mathcal{P}_t$  in eq. (4) with a transformer  $\mathcal{P}_{\text{transf}}$ . Transformers [135] have been shown effective for representing sequential inputs in the NLP domain [62, 81, 113, 114]. After spatial averaging, the output  $\mathbf{h} = \mathcal{P}_s(\Psi(\tilde{\mathbf{v}})) \in \mathbb{R}^{D \times T_1}$  of the network has one feature vector per time step, and is thus amenable to processing by a transformer. The feature  $\mathbf{h}$ , which differs in latent time-dimension size from its uncropped variant can be seen as masking the transformer’s attention. Masking attention has been used in transformer encoder-decoder training to prevent the model from cheating [33] and encourage it to leverage information from the context. We use a shallow and light-weight transformer on top of our feature cropping procedure, which we show to be sufficient to reap the benefit of better temporal modelling incurring only a very small computational cost. We use 2-layers and 4 self-attention heads and provide further details on the transformer architecture in the Appendix.

### 3.4. Overall loss

Our combined model, **STICA**, better learns space-time invariances and relationships by cropping in space-time and leveraging temporal attention with a transformer. For training, we sample  $N$  videos in a batch and, for each of them, compute two ‘large’ visual crops in RGB space,  $2(n+m)$  small and medium feature crops (Sec. 3.2), and an audio augmentation  $a$ . With those, the overall objective is obtained by summing the within-modality loss  $L_{vv}$  from eq. (6) to the cross modality losses:

$$L = \lambda_{vv}L_{vv} + \lambda_{va}L_{va}, \quad (7)$$

where  $L_{va} = \mathcal{L}(v_{L_1}, a) + \mathcal{L}(v_{L_2}, a) + \mathcal{L}(a, v_{L_1}) + \mathcal{L}(a, v_{L_2})$ .

## 4. Experiments

We first describe the datasets (Sec. 4) and implementation details (Sec. 4) for pretraining. In Sec. 4.1, we describe the downstream tasks for evaluating the representation obtained from self-supervised learning. In Sec. 4.2, we ablate the various components of our method, and the importance of temporal context and multi-modality in Sec. 4.3. Lastly, in Sec. 4.4, we compare with prior work in video and multi-modal representation learning.

**Data.** We pretrain on the Kinetics-400 dataset [69], which contains about 230K training videos and 13K validation videos belonging to 400 action classes. This dataset is the ‘ImageNet’ for video representation learning due to its moderate size and being public, allowing for broad access and comparability. After pretraining, we evaluate using video action retrieval and action recognition on HMDB-51 [77] and UCF-101 [120]. HMDB-51 [77] consists of 7K

video clips spanning 51 different human activities. HMDB-51 has three train/test splits of size 5K/2K respectively. UCF-101 [120] contains 13K videos from 101 human action classes, and has three train/test splits of size 11K/2K respectively.

**Implementation details.** Following [106], we use the R(2+1)-18 [133] network as visual encoder and ResNet [59] with 9 layers as audio encoder. We train for 100 epochs and use 30 frames with temporal stride of 1 at sampling rate of 30fps at spatial resolution of  $112 \times 112$  as input. In our ablations, we evaluate the learned representation by finetuning the visual encoder on fold 1 of the HMDB-51 [77] action recognition dataset. Further implementation details are given in the Appendix.

### 4.1. Downstream tasks

**Video action retrieval.** For video retrieval, we follow the standard protocol described in [145]. We use the split 1 of UCF-101, and additionally HMDB-51. We uniformly sample 10 clips per video, max pool and then average the features after the last residual block for each clip per video. We use these averaged features from the validation set to query the videos in the training set. If the class of a retrieved video matches the class of query video, we count it as a match. We measure recall at  $k=1, 5, 20$ .

**Video action recognition.** As is standard in the literature, we evaluate our pretrained representations by finetuning our visual backbone on the video action recognition task on HMDB-51 and UCF-101 datasets. We closely follow the finetuning schedule of GDT [106]. During finetuning, we use SGD with initial learning rate 0.0025, which we gradually warm up to 0.02 in the first 2 epochs. The weight decay is set to 0.005 and momentum to 0.9. We use a mini-batch size of 32 and train for 12 epochs with the learning rate multiplied by 0.05 at 6 and 10 epochs. For training, we randomly sample 1s clips per video, and during evaluation, we uniformly sample 10 clips from each video and apply 3-crop evaluation as in [41].

### 4.2. Comparison experiments and ablations

**Cropping augmentation.** In Tab. 1a, we ablate the importance of spatial augmentation in learning video representations. We compare our proposed Feature Crop augmentation,  $C_{\bar{B}}$ , to the recently proposed Multi-Crop augmentation strategy [20] and other baseline approaches. Multi-Crop has proven to be effective in image self-supervised learning because it forces the model to learn local-to-global associations, by explicitly enforcing invariance between features of large-crops and those of multiple small crops. While effective, it can be particularly computationally intensive, which, with our hardware, limits its use to only two large crops and one small crop when applied to video representation learn-

**Table 1: Comparison experiments and ablations.** We compare key parameters and settings of our proposed method. We report results model performance at epoch 100 and with 30 frames and without transformer unless noted otherwise.

Cropping-strategy	Resolution	GPU-h/epoch	Acc.	$l$ -Spatial size		$l$ -Temporal size		Acc.
				$M$	$S$	$M$	$S$	
Default	$1 \times 112^2$	17.3	54.0	$1 \times 7^2$		$1 \times 4$		54.0
Two RGB Crops	$2 \times 112^2$	29.3	58.6	$1 \times 6^2$	$2 \times 4^2$	$1 \times 4$		59.9
Multi RGB Crops [20]	$2 \times 112^2 + 1 \times 96^2$	46.7	59.3	$1 \times 6^2$	$2 \times 4^2$	$2 \times 3$	$1 \times 2$	58.4
Ours (Feature Crop)	$2 \times 112^2 + \text{latent}$	29.3	<b>60.4</b>	$2 \times 6^2$	$4 \times 4^2$	$2 \times 3$	$1 \times 2$	<b>60.4</b>

(a) **Cropping** yields benefits but requires more compute. Our feature crops are efficient *and* outperform [20]. Note that all models are trained for 100 epochs.

(b) **Feature crops.** Heavier augmentations in latent ( $l$ ) space and time lead to better representations.

Pretraining	Finetuning	Acc.	Transf.?	Layers	Params	GFLOPS	Acc.	$C_{\text{space}}$	$C_{\text{time}}$	T?	Acc.
$\mathcal{P}_t$	$\mathcal{P}_t$	54.0	✗	0	37.2M	77.7	54.0	✗	✗	✗	54.0
$\mathcal{P}_t$	$\mathcal{P}_{\text{transf}}$	54.6	✗	0	42.8M	80.0	57.3	✓	✗	✗	59.9
$\mathcal{P}_{\text{transf}}$	$\mathcal{P}_t$	52.1	✓	2	42.4M	77.8	<b>60.3</b>	✓	✓	✗	60.4
$\mathcal{P}_{\text{transf}}$	$\mathcal{P}_{\text{transf}}$	<b>60.3</b>	✓	4	47.7M	77.8	58.3	✓	✓	✓	<b>62.0</b>

(c) **Pooling.** Compared to Average-Pooling ( $\mathcal{P}_t$ ), Transformer-based pooling ( $\mathcal{P}_{\text{transf}}$ ) gives stronger performance.

(d) **Architecture.** Using up to two transformer layers gives gains, not due to more trainable parameters.

(e) **Combined gains.** Feature crop in space  $C_{\text{space}}$  and time  $C_{\text{time}}$  and transformer pooling (T) add cumulative benefits.

Method	RGB-Crops			Multi-scale RGB-Crops			Feature Crops	
	1x	2x	4x*	$2 \times 112 + 1 \times 96$	$2 \times 112 + 2 \times 96$	$2 \times 112 + 6 \times 96^*$	(1x7, 1x4)	(2x6 + 4x4, 2x3 + 1x2)
GPU-h/epoch	17.3	29.3	60.0	46.7	53.3	100.7	29.3	30.0

(f) **Speed.** Input-crops are slow: \* methods require reducing batch sizes (see Appendix) as activations do not fit on GPU.

ing. Our proposed Feature Crop is not only more efficient, but outperforms Multi-Crop by 1.1% when the learned representations is applied to action classification in HMDB-51. By cropping in feature space, we achieve a similar effect but can increase the number of small crops from 1 to 6 without increasing compute time.

**Feature crop parameters.** In Tab. 1b, we study the parameters of our Feature Cropping approach. We find that even our basic variant, which does one medium  $6 \times 6$  crop and two  $4 \times 4$  small crops (by cropping a  $7 \times 7$  tensor) increases performance by nearly 6%, which is a relative improvement of more than 10%. If we further increase the number of crops in time and space, the performance increases from 59.9% to 60.4%.

**Pooling Function.** In Tab. 1c, we test temporal aggregation. We find that using a shallow transformer significantly outperforms simple average pooling by more than 5%; however, transformer pooling must be used both for pre-training the representation and for finetuning it on the target dataset.

**Transformer architecture.** In Tab. 1d, we test variants of the transformer architecture, including ablating it altogether. We find that temporal modelling as measured by downstream performance peaks at two layers, likely due to optimization difficulties of deeper transformers with SGD. We also compare to a model with approximately the same number of parameters as our 2-layer transformer (achieved by increasing the networks' last block's hidden dimension

to 640). We find that the transformer still yields gains of 3%, indicating that it not the number of parameters but the modelling of time that is crucial for strong performance.

**Combining Feature Crops and Transformer Pooling.** In Tab. 1e, we show that combining Feature Crops in space and time, and then adding transformer pooling yield additive gains, with the best result obtained by combining all effects (which corresponds to **STiCA**). This shows that space-time augmentations and transformer pooling are complementary.

**Cropping efficiency.** In Tab. 1f, we compare training times (normalized to GPUs $\times$ hours) for Kinetics-400 epochs for the various spatial crops considered. We make two observations: First, the compute cost of RGB crops scales proportionally to their number because a full forward pass is required for each crop. Second, using a larger number of RGB crops eventually requires to decrease the batch size, which increases significantly the training time. In contrast, the cost of Feature Crop remains roughly constant no matter the number of crops.

### 4.3. Temporal Context and Multi-modality

**Length of temporal context.** In Tab. 2, we show the importance of leveraging longer context to improve video self-supervised representation learning. Similar to the supervised regime [134, 139], we observe improved accuracy as we increase the number of frames used during pretraining and fine-tuning. More importantly, the transformer pooling

Frames		Accuracy	
Pretrain	Finetune	GAP	Transf.
30	30	54.0	<b>60.3</b>
60	60	62.4	<b>66.1</b>
90	90	58.0	<b>66.9</b>

**Table 2: Temporal context.** We report results with different number of frames on finetuning accuracy.

$\lambda_{va}$	$\lambda_{vv}$	F. Crop?	Acc.
0	1	No	43.3
1	0	No	54.0
0.5	0.5	No	58.6
0.5	0.5	Yes	<b>60.3</b>

**Table 3: Loss.** Combining within-modal and cross-modal loss with Feature-crops is key.

Method	Architecture	Dataset	Top-1 Acc%	
			HMDB	UCF
Supervised	R(2+1)D-18	K-400	70.4	95.0
SeLaVi [9]	R(2+1)D-18	K-400	47.1	83.1
TempTrans [63]	R3D-18	K-400	49.8	79.3
PEMT [80]	SlowFast	K-400	-	85.2
XDC [6]	R(2+1)D-18	K-400	52.6	86.2
MemDPC [53]	R-2D3D	K-400	54.5	86.1
AVSF [143]	AVSF	K-400	54.6	87.0
AVTS [74]	MC3-18	K-400	56.9	85.8
CPD [85]	R3D-50	K-400	57.7	88.7
AVID [97]	R(2+1)D-18	K-400	60.8	87.5
GDT [106]	R(2+1)D-18	K-400	60.0	89.3
ACC [90]	R3D-18	K-400	61.8	90.2
GLCM [91]	R3D-18	K-400	61.9	91.2
CoCLR [54]	S3D	K-400	62.9	90.6
CVLR [112] <sup>3</sup>	R3D-50	K-400	66.7	92.2
<b>Ours: STiCA</b>	R(2+1)D-18	K-400	<b>67.0</b>	<b>93.1</b>
<hr/>				
SeLaVi [9]	R(2+1)D-18	VGGs	53.1	87.7
Speech2Act [98]	S3D-G	Movie	58.1	-
DynamoNet [34]	ResNext101	Y8M	58.6	87.3
MIL-NCE [93]	S3D	HT	61.0	91.3
AVTS [74]	MC3-18	AS	61.6	89.0
AVID [97]	R(2+1)D-18	AS	64.7	91.5
Textual [123]	S3D-G	WVT-70M	65.3	90.3
GDT [106]	R(2+1)D-18	AS	66.1	92.5
ACC [90]	R(2+1)D-18	AS	67.2	93.5
ELo [110]	R(2+1)D-50	Y2M	67.4	93.8
XDC [6]	R(2+1)D-18	IG65M	68.9	95.5
GDT [106]	R(2+1)D-18	IG65M	72.8	95.2
MMV [5]	TSM-50x2	AS+HT	75.0	95.2

**Table 4: Comparison to SoTA for action recognition.** Dashed line indicates position of our Kinetics-400 model in comparison to models trained with many more videos. We follow standard evaluation protocol across 3-folds. For linear evaluation results see Tab. 7.

layer is better able to exploit this additional context, outperforming average pooling by over 4% for all frame lengths. Notably, there is a drop in performance when using GAP for extremely long contexts (90 frames).

**Loss.** Lastly, in Tab. 3, we study the effect of combining multi-modal learning signals with our contributions. In the first row, we have the baseline of naively extending Sim-

<sup>3</sup>Concurrent work.

Recall @	UCF			HMDB		
	1	5	20	1	5	20
MemDPC [53]	20.2	40.4	64.7	7.7	25.7	57.7
VSP [25]	24.6	41.9	62.7	10.3	26.6	76.8
SeLaVi [9]	52.0	68.6	84.5	24.8	47.6	75.5
CoCLR [54]	55.9	70.8	82.5	26.1	45.8	69.7
GDT [106]	57.4	73.4	88.1	25.4	51.4	75.0
<b>Ours: STiCA</b>	<b>59.1</b>	<b>76.2</b>	<b>88.1</b>	<b>26.3</b>	<b>49.2</b>	<b>76.4</b>

**Table 5: Comparison to SoTA for retrieval.** Nearest neighbor action retrieval performance @  $k = \{1, 5, 20\}$ .

CLR [24] to the video domain, by learning invariances to spatial augmentations of two large-crops. Compared to this, the cross-modal baseline (row 2) already achieves gains of more than 10%. While adding a within-modal invariance adds another 4.6%, we find that the best performance is obtained with our feature crops, adding another 1.7% in performance and showing its unique potential to supplement cross-modal signals.

#### 4.4. Comparison with the state of the art

**Video Action Recognition.** In Tab. 4, we evaluate our pretraining approach on the standard HMDB-51 and UCF-101 action recognition benchmarks after pretraining on the Kinetics-400 dataset. Firstly, we find our model outperforming the similar NCE-based GDT [106] model by 7.0% and 3.8% on HMDB-51 and UCF-101. We further significantly outperform the current state-of-the-art methods CoCLR [54] by 4.1% and 2.5% and CVLR [112] by 2.6% and 1.0% on HMDB-51 and UCF-101, respectively. Even more impressively, our approach is able to outperform most prior works that use AudioSet [44] pre-training, which is around 10 $\times$  larger than Kinetics-400. This shows how effective and data-efficient our approach is, significantly closing the gap to supervised learning.

**Video Action Retrieval.** Lastly, we directly evaluate the transfer-ability of our pretrained representations on action retrieval on UCF-101 and HMDB-51. Similarly to full finetuning setting, we outperform all prior works.

## 5. Conclusion

We have address two shortcomings of current self-supervised video representation learning: insufficient spatial invariance, especially compared to the image domain, and inadequate modelling of time. We have introduced STiCA, improving spatial invariance at very little cost by implementing cropping in feature space, and improving modelling of time via a shallow transformer. Our method brings self-supervised video representation learning one step closer to the supervised case, providing significant gains w.r.t. the state-of-the-art.



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