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

Mandela Patrick*, Po-Yao Huang*, Ishan Misra, Florian Metze, Andrea Vedaldi
Facebook AI Research
mandelapatrick, berniehuang, imisra, fmetze, vedaldi@fb.com

Yuki M. Asano*, João Henriques
Oxford University
yuki, joao@robots.ox.ac.uk

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 naive 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 available1.

1. Introduction

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

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*Equal contribution.

1https://github.com/facebookresearch/GDT
resentations, 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 (~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 particular 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, 125, 126, 126] data. Multimodal 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 convolution 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, 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 \( \mathcal{B} = \{x_1, \ldots, x_N\} \) of data samples. Slightly modifying [24], for each sample \( x_i \), draw a set of random nuisance transformations \( \{g_{ai}\}_{1 \leq i \leq N} \) and let \( z_{ai} = \Phi(g_{ai}(x_i)) \) be the representations of the transformed samples. Likewise, consider a second set \( \beta \) of transformations \( \{g_{bi}\}_{1 \leq i \leq N} \). The noise contrastive loss (NCE) is given by:

\[
    L(\alpha, \beta) = -\frac{1}{N} \sum_{i=1}^{N} \log \frac{e^{\alpha \beta_i \text{sim}(z_{ai}, z_{bi})}}{\sum_{j=1}^{N} e^{\alpha \beta_j \text{sim}(z_{ai}, z_{bj})}}
\]
Previous methods (AVTS, XDC, MIL-NCE, AVID, GDT etc.)

- Video
- Video
- 3D CNN
- Global Spatial & Temporal Pooling
- Cross-modal SSL Loss

STICA

- Video
- Video
- 3D CNN
- Spatial pool
- Shallow Transformer
- Temporal Attention
- Cross-modal SSL Loss
- Within-modal SSL Loss

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., $L(\alpha, \beta) \neq L(\beta, \alpha)$). Note also that we can introduce any number of transformation sets $\alpha, \beta, \gamma, \ldots$ 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 $x = (v, a)$ consists of a visual component $v$ and an audio component $a$. One considers two sets of transformations $g_v$, extracting and augmenting the visual component, and $g_a$, extracting and augmenting the audio component. We still write $\Phi(g_v(x))$ for the feature computed for either visual and audio components, but the symbol means that a modality-specific neural network is applied as needed.\(^2\)

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:

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

(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 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 $x \in \mathbb{R}^{3 \times H \times W}$ with three channels and height $H$ and width $W$ respectively, a crop is given by a box $B = (x_{\min}, x_{\max}, y_{\min}, y_{\max})$. The image tensor is first cropped as:

$$C_B(x) = x_{[:, y_{\min}:y_{\max}, x_{\min}:x_{\max}}$$

(3)
where the \( : \) symbol is used to denote an index range. The cropped tensor is then resized to a tensor \( \tilde{x} = g(x) = R_{H_0,W_0}(C_B(x)) \in \mathbb{R}^{3 \times H_0 \times W_0} \) 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 \( \nu \in \mathbb{R}^{3 \times T \times H \times W} \) 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 \( B = (x_{\text{min}}, x_{\text{max}}, y_{\text{min}}, y_{\text{max}}, t_{\text{min}}, t_{\text{max}}) \) and define \( \tilde{\nu} = g_\nu(\nu) = R_{H_0,W_0}(C_B(\nu)) \in \mathbb{R}^{3 \times T \times H_0 \times W_0} \) by extending (3) in the obvious way.

The deep neural network \( z = \Phi(\tilde{\nu}) \) mapping \( \nu \) to its corresponding code \( z \) 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

\[
\Phi(\tilde{\nu}) = (\mathcal{P}_t \circ \mathcal{P}_s \circ \Psi)(\tilde{\nu}) \quad (4)
\]

Here, the first function is a 3D convolutional neural network \( \Psi(\tilde{\nu}) \in \mathbb{R}^{D \times T \times H_1 \times W_1} \) 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 \( \alpha, \beta \), two different space-time crops \( g_{\nu_1}(\alpha) = g_{\nu_1}(\beta) \), each corresponding to random tubes \( B_1 \) and \( B_2 \) respectively. The tubes are not sampled independently, however, as they have the same temporal extent \( (t_{\text{min}}, t_{\text{max}}) \).

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 \( \tilde{\nu} = R_{H_0,W_0}(C_B(\nu)) \in \mathbb{R}^{D \times T_1 \times H_1 \times W_1} \). Then we can efficiently construct a new view of this data by applying the Feature Crop \( C_B \) directly on each intermediate representation, yielding

\[
\tilde{\nu} = C_B(\tilde{\nu}) = \Psi(\tilde{\nu})([\text{min}-\text{max}, \text{min}-\text{max}, \text{min}-\text{max}]) \quad (5)
\]

Since the operator \( C_B \) 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 \( \nu \), 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 \( \mathcal{T}_i = \{M_1 L_1, \ldots, M_m L_1, S_1 L_1, \ldots, S_n L_1\} \). 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:

\[
\mathcal{L}^{vw} = \sum_{\alpha, \beta} \mathcal{L}(v_\alpha, v_\beta) + \mathcal{L}(v_\beta, v_\alpha), \quad \text{where} \quad (\alpha, \beta) \in (\mathcal{T}_1 \times \mathcal{T}_2) - (S_1 \times S_2) \quad (6)
\]

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 \( P_t \) in eq. (4) with a transformer \( P_{\text{trans}} \). Transformers [135] have been shown effective for representing sequential inputs in the NLP domain [62, 81, 113, 114]. After spatial averaging, the output \( h = P_s(\Psi(\bar{v})) \in \mathbb{R}^{D \times T_1} \) of the network has one feature vector per time step, and is thus amenable to processing by a transformer. The feature \( h \), 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 \( L_{vuv} \) from eq. (6) to the cross modality losses:

\[
L = \lambda_{vuv}L_{vuv} + \lambda_{va}L_{va},
\]

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

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, \( C_F \), 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-
In Table 1, 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. |
|--------------------|------------|-------------|------|
| Default            | 1 × 112²   | 17.3        | 54.0 |
| Two RGB Crops      | 2 × 112²   | 29.3        | 58.6 |
| Multi RGB Crops [20] | 2 × 112² + 1 × 96² | 46.7 | 59.3 |
| Ours (Feature Crop) | 2 × 112² + latent | 29.3 | 60.4 |

(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.

| Pretraining | Finetuning | Acc. | Transf.? | Layers | Params | GFLOPS | Acc. |
|-------------|------------|------|----------|--------|--------|--------|------|
| \( P_t \)     | \( P_t \)     | 54.0 | ✗        | 0      | 37.2M  | 77.7   | 54.0 |
| \( P_t \)     | \( P_{trans} \) | 54.6 | ✗        | 0      | 42.8M  | 80.0   | 57.3 |
| \( P_{trans} \) | \( P_{trans} \) | 52.1 | ✓        | 2      | 42.4M  | 77.8   | 60.3 |
| \( P_{trans} \) | \( P_{trans} \) | 60.3 | ✓        | 4      | 47.7M  | 77.8   | 58.3 |

| Method | RGB-Crops | Multi-scale RGB-Crops | Feature Crops |
|--------|-----------|-----------------------|---------------|
|        | 1x 2x 4x² | 2x112 + 1x96 2x112 + 2x96 2x112 + 6x96² | (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 |

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

(c) **Pooling.** Compared to Average-Pooling (\( P_t \)), Transformer-based pooling (\( P_{trans} \)) 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 \( C_{space} \) and time \( C_{time} \) and transformer pooling (T) add cumulative benefits.

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

Our proposed Feature Crop is not only more efficient, but outperforms Multi-Crop by 1.1% when the learned representations are 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×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
Different number of frames on fine-tuning accuracy.

Table 2: Temporal context.

We report results with different number of frames on fine-tuning accuracy.

| Frames | Pretrain | Finetune | Accuracy |
|--------|----------|----------|----------|
| 30     | 30       | 54.0     | 60.8     |
| 60     | 60       | 62.4     | 66.1     |
| 90     | 90       | 58.0     | 66.9     |

Table 3: Loss.

Combining within-modal and cross-modal loss with Feature-crops is key.

| λ_{vv} | λ_{cv} | F. Crop? | Acc.  |
|--------|--------|----------|-------|
| 0      | 0      | No       | 43.3  |
| 0.5    | 0      | No       | 54.0  |
| 0.5    | 0.5    | No       | 58.6  |
| 0.5    | 0.5    | Yes      | 60.3  |

Table 4: Comparison to SoTA for action recognition.

Dashed line indicates position of our Kinetics-400 model.

| Method               | Architecture | Dataset | Top-1 Acc% |
|----------------------|--------------|---------|------------|
| SeLaVi [9]           | R(2+1)D-18  | K-400   | 70.4       |
| TempTrans [63]       | R3D-18      | K-400   | 49.8       |
| PEMT [80]            | SlowFast    | K-400   | 54.5       |
| XDC [6]              | R(2+1)D-18  | K-400   | 54.4       |
| MemDPC [53]          | R-2D3D      | K-400   | 54.6       |
| AVSF [143]           | AVSF        | K-400   | 54.6       |
| AVTS [74]            | MC3-18      | K-400   | 54.6       |
| CPD [85]             | R3D-50      | K-400   | 57.7       |
| AVID [97]            | R(2+1)D-18  | K-400   | 60.8       |
| GDT [106]            | R(2+1)D-18  | K-400   | 60.0       |
| ACC [99]             | R3D-18      | K-400   | 61.8       |
| GLCM [91]            | R3D-18      | K-400   | 61.9       |
| CoCLR [54]           | S3D         | K-400   | 62.9       |
| CVLR [112]           | R3D-50      | K-400   | 66.7       |
| **Ours: STiCA**      | R(2+1)D-18  | K-400   | **67.0**   |

| Method               | Architecture | Dataset | Top-1 Acc% |
|----------------------|--------------|---------|------------|
| SeLaVi [9]           | R(2+1)D-18  | VGGS    | 53.1       |
| Speech2Act [98]      | 3D-G Movie   |         | 58.1       |
| DynamoNet [34]       | ResNext101   | YSM     | 58.6       |
| MIL-NCE [93]         | S3D HT       |         | 61.0       |
| AVTS [74]            | MC3-18      | AS      | 61.6       |
| AVID [97]            | R(2+1)D-18  | AS      | 64.7       |
| Textual [123]        | S3D-G WVT-70M|         | 65.3       |
| GDT [106]            | R(2+1)D-18  | AS      | 66.1       |
| ACC [90]             | R(2+1)D-18  | AS      | 67.2       |
| ELO [110]            | R(2+1)D-50  | Y2M     | 67.4       |
| XDC [6]              | R(2+1)D-18  | IG6SM   | 68.9       |
| GDT [106]            | R(2+1)D-18  | IG6SM   | 72.8       |
| MMV [5]              | TSM-50x2 AS+HT|        | 75.0       |

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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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6. Appendix

6.1. Implementation Details

While videos in Kinetics are 10 seconds long, we randomly sample either 1-second (30 frames), or 2-second (60 frames) clips from the 30fps videos. For the R(2+1)-D-18 visual encoder, the dimensions of the res5 feature map before spatial pooling is \( 512 \times 7 \times 7 \) for a 112 \( \times \) 112 resolution video, where \( T = 4 \) for 30-frame (1 second) input, and \( T = 8 \) for 60-frame (2 second) input. After spatial pooling, we use either average pooling or a transformer as the temporal pooling function for the visual encoder, but always use average pooling for the audio encoder. The transformer’s layers dimensionality are set to 512-D. Both encoders produce a fixed-dimensional representation vectors after temporal aggregation (512-D). Both vectors are then passed through two fully-connected layers with intermediate size of 512 to produce 256-D embedding vectors \( z \) as in [106]. We use these embeddings in our loss eq. (7) and train our model for 100 epochs. For the visual component of the video, we use a 30 frame RGB clip as input, at 30 fps covering 1 second. The video clip has a spatial resolution of \( 112 \times 112 \) pixels. For input data augmentation, we apply random crops, horizontal flips, Gaussian blur and color jittering, all clip-wise consistent, following the protocol of SimCLR [24], and we ablate multiple settings for spatial and temporal feature cropping sizes. For the audio input, we extract a 1-second log-mel spectrogram of dimension 257 \( \times \) 199 starting at the same time as the visual component. We also apply volume jittering to increase the robustness of our audio features. We optimize this model using SGD with momentum 0.9, weight decay \( 10^{-5} \) and learning rate 0.04, with a warm-up period of 10 epochs. For NCE contrastive learning, the temperature \( \tau \) is set as 0.1 for cross-modal loss, and 0.5 for the within-modal loss. We use a mini-batch size of 8 on each of our 64 GPUs giving an effective batch size of 512 for distributed training. In our ablations, we evaluate the learned representation by fine-tuning the visual encoder on fold 1 of the HMDB-51 [77] action recognition dataset.

6.1.1 State-of-the-Art Experiment Details

For our state-of-the-art model, we train for 100 epochs, using R(2+1)-D-18 visual encoder with transformer temporal attention pooling, and Resnet-9 for audio encoder. We use 60 frames as input, and feature-crop augmentation (space: \( 2 \times 6^2 + 4 \times 4^2 \) & time: \( 2 \times 3 + 1 \times 2 \)).

6.2. Transformer Architecture Details

We use a 2-layer transformer, with 4 attention heads, and hidden dimension 512. The input to the transformer is the spatially averaged output of the last convolutional layer of

| Method                  | Pretraining | Acc% |
|-------------------------|-------------|------|
| Ours: STiCA            | K400        | 94   | 81.1 |
| SoundNet [12]          | SNet        | 88   | 74.2 |
| L3-Net [7]             | SNet        | 93   | 79.3 |
| AVTS [74]              | SNet        | 94   | 82.3 |
| DMC [60]               | SNet        | –    | 82.6 |
| AVTS [74]              | AS          | 93   | 80.6 |
| XDC [6]                | AS          | –    | 85.8 |
| MMV [5]                | AS          | –    | 86.1 |
| AVID [97]              | AS          | 96   | 89.2 |
| GDT [106]              | AS          | 98   | 88.5 |
| ACC [90]               | AS          | –    | 90.8 |
| Human [109]            | –           | –    | 81.3 |

Table 6: Audio classification. Downstream task accuracies on standard audio classification benchmarks on DCASE2014 and ESC50. Dataset abbreviations AudioSet, Kinetics400, SoundNet.
strate competitive performance relative to the state-of-the-art, despite training on a much smaller and less audio-rich Kinetics-400 dataset. We extract 10 equally spaced 2-second sub-clips from each full audio sample of ESC-50 [109] and 60 1-second sub-clips from each full sample of DCASE2014 [122]. We save the activations that result from the audio encoder to quickly train the linear classifiers. We use activations after the last convolutional layer of the ResNet-9 and apply a max pooling with kernel size (1,3) and stride of (1,2) without padding to the output. For both datasets, we then optimize a L2 regularized linear layer with batch size 512 using the Adam optimizer [72] with learning rate $1 \times 10^{-4}$, weight decay set to $5 \times 10^{-4}$ and the default parameters. The classification score for each audio sample is computed by averaging the sub-clip scores in the sample, and then predicting the class with the highest score. The mean top-1 accuracy is then taken across all audio clips and averaged across all official folds.

### 7.2. Linear probing results

In Tab. 7, we compute the linear classification results of our model compared to other recent methods. We find that our best model has competitive 3-fold linear evaluation results of 48.2% on HMDB-51 and 77.0% on UCF-101.

| Method   | Architecture | Dataset | Top-1 Acc%  |
|----------|--------------|---------|-------------|
|          |              |         | HMDB UCF    |
| RotNet3D [65] | S3D         | K600    | 24.8 47.7   |
| CBT [125]    | S3D+BERT    | K600    | 29.5 54.0   |
| MemDPC [53]  | R-2D3D      | K400    | 30.5 54.1   |
| AVSF [143]   | AVSF        | K400    | 44.1 77.4   |
| CoCLR [54]   | S3D         | K400    | 46.1 74.5   |
| **Ours: STiCA** | R(2+1)D-18 | K400    | **48.2 77.0** |
| MIL-NCE [93] | S3D         | HT      | 53.1 82.7   |
| XDC [6]      | R(2+1)D-18  | IG65M   | 56.0 85.3   |
| MMV [5]      | R(2+1)D-18  | AS      | 60.0 83.9   |
| ELo [110]    | R(2+1)D-50  | Y8M     | 64.5 –      |

Table 7: Comparison to state-of-the-art. Transfer learning results on UCF-101 and HMDB-51 when video backbone is frozen.

### 7.3. Supervised training on K-400

Here we experiment with training supervisedly on Kinetics-400 and observing the effect of using feature cropping (with the configuration 2 medium and 2 small latent space crops). The experimental results are given in Tab. 8. We find that even though our method is designed for contrastive cross-modal pretraining, using feature crops can help in training in a supervised manner too.

| Fm-Crop | HMDB-51 Top-1 Acc. |
|---------|---------------------|
| ❗️       | 67.6                |
| ✓        | 69.0                |

Table 8: Supervised Training. We train the R(2+1)D+Transformer architecture supervisedly on Kinetics-400 with and without feature crops enabled.

### 7.4. Audio-Visual Heatmap Visualizations

In Fig. 3, we show examples that our model truly learned some spatial correspondence between a region and audio. We have done this by visualizing the strength of the dot-product of the visual feature map (without pooling) with the audio feature vector.

Figure 3: Heatmap visualizations. Heatmaps are obtained by removing the spatial pooling layer and visualizing the strength of the dot-product of the audio feature vector with the video feature-map as in [8]. Here, we show selected samples from Kinetics-400 training set of the resulting heatmaps along with the middle frame of the video.

### 7.5. Preventing Shortcut Learning with Feature Crops.

Noise contrastive learning works better when you can reduce the mutual information between the input pairs [131] as its harder for the network to cheat. This can be achieved by taking multiple spatial crops of images in the input space and independently applying different augmentations, such as color jittering and Gaussian blurring, to the cropped inputs. However, as mentioned above, taking more than 2 crops in input space is both memory and computationally infeasible for multi-modal video data. Crops in feature space, on the other hand, allows us to take multiple crops for noise contrastive learning. However, since CNNs have large receptive fields that easily cover the full frame, there may be shortcut learning with feature crops as information may...
leak between the crops from same feature map. To alleviate this, we take feature crops from two originally augmented video clips, allowing us to make NCE comparisons across modalities and individual augmentations (such as color jitter), leading to a beneficial reduction in mutual information. Furthermore, while the theoretical receptive fields of units in later layers are indeed very large, units tend to be sensitive to an effective area which is significantly smaller than the theoretical receptive field [89, 153], further reducing the mutual information between inputs for noise contrastive learning.