Broaden Your Views for Self-Supervised Video Learning

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Abstract

Most successful self-supervised learning methods are trained to align the representations of two independent views from the data. State-of-the-art methods in video are inspired by image techniques, where these two views are similarly extracted by cropping and augmenting the resulting crop. However, these methods miss a crucial element in the video domain: time. We introduce BraVe, a self-supervised learning framework for video. In BraVe, one of the views has access to a narrow temporal window of the video while the other view has a broad access to the video content. Our models learn to generalise from the narrow view to the general content of the video. Furthermore, BraVe processes the views with different backbones, enabling the use of alternative augmentations or modalities into the broad view such as optical flow, randomly convolved RGB frames, audio or their combinations. We demonstrate that BraVe achieves state-of-the-art results in self-supervised representation learning on standard video and audio classification benchmarks including UCF101, HMDB51, Kinetics, ESC-50 and AudioSet.

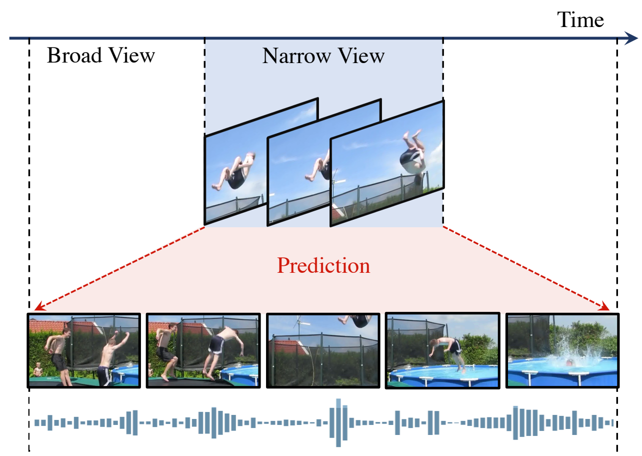

Figure 1. Given a *narrow view* corresponding to a video clip of a few seconds, **BraVe** is tasked with predicting a *broad view* that spans a longer temporal context of the video in different modalities (here visual and audio). Solving that task requires the representation to extrapolate what happened before, during and after the *narrow view*, and results in state-of-the-art video representations.

1. Introduction

Over the past few years, self-supervised methods have revolutionized the field of representation learning [17, 36, 68]. These methods directly learn from data without the need for manually defined labels that are hard to get at scale. Doing so, one can successfully leverage large amounts of *uncurated* data to improve representations. Even more importantly, self-supervised learning enables richer training tasks to be defined, compared to the standard approach of trying to categorize diverse visual inputs into a fixed set of categories. This has led to self-supervised representations outperforming supervised ones on downstream tasks [33]. Video is a natural domain for self-supervised learning since data is rich and abundant but hard to annotate at scale due to the additional temporal complexity. However, most methods in the video domain take direct inspiration from methods developed for images without fully taking advantage of its distinctly different dimension: time.

In particular, one common aspect of self-supervised methods for images is to extract two views from a given instance using the same general augmentation procedure, feed them into a shared backbone, and extract a supervisory signal from the fact that these two views originate from the same source. This is true for most recent approaches irrespective of their underlying learning principle: contrastive approaches [17], clustering-based method [13], or regression algorithms [68]. The same principle has been followed in the video domain [4, 67]. Specifically, most video methods extract the different views from a source video clip in a *symmetric* fashion with respect to time: all extracted views have the same temporal extent in the video [4, 23, 45, 67]. However, doing so does not benefit from learning from information contained at different time scales.

In this paper, we introduce an algorithm dubbed

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“**Bro**a**d**en your **V**i**e**ws” (**BraVe**), that breaks this symmetry in order to improve representation learning from videos. In detail, given a *narrow view* corresponding to a video clip of a few seconds, **BraVe** learns a representation by predicting a *broad view* that spans the longer temporal context of the full video clip as illustrated in Figure 1. Solving such a task requires extrapolating to the general context in which a given event occurs. In the example of Figure 1, one has to predict what happened before the person is in the sky (they probably jumped with the help of some device, given the height), as well as what is going to happen next (they will probably fall down somewhere soft) in order to solve the task. This task arguably requires a good understanding of the structure of events and is therefore a promising task for learning representations. While related local-to-global proxy tasks have been studied in the image domain via network architectural designs [9, 37] or multi-size cropping [17], applying these techniques to videos is not straightforward, because of the increased computational complexity incurred by the time dimension and the artifacts introduced when doing similar resize operations in spatio-temporal volumes. To address this challenge, we propose to process broad views with a dedicated model. We demonstrate that under a fixed computational budget, learning from the supervision provided by our broad views performs better than alternatives relying on symmetric augmentation procedures. Our algorithm is simple and does not require a cumbersome creation of explicit negatives as in contrastive methods. Instead we use a direct regression-based approach inspired by BYOL [29], where the views are processed by dedicated backbones and regress each other. Breaking the symmetry enables the use of stronger augmentations and different modalities for the broad view, which improves the quality of the final representations.

Contributions. We make the following contributions: **(i)** We propose a novel framework for representation learning, called **BraVe**, which generates views at different time scales and learns representations via simple regression across views, **(ii)** We explore using different augmentations and modalities in the broad view such as audio, flow or randomly convolved RGB frames. **(iii)** We evaluate this framework in the video domain, both with and without audio as an auxiliary supervisory signal, where we obtain *state-of-the-art* results on video and audio classification benchmarks UCF101, HMDB51, Kinetics, ESC-50 and AudioSet.

2. Related work

Image-based self-supervised learning. Most successful self-supervised methods learn a representation by defining a *pretext task*, whose resolution typically entails learning useful representations [13, 14, 19, 20, 28, 58, 61, 89]. In particular, contrastive methods have provided spectacular performance [10, 17, 21, 33, 36, 39, 47, 55, 78, 79]. Contrastive methods learn by pulling representations of different transformations of the same image (positive instances) closer, and pushing representations of different images (negatives) apart [10, 59]. The main drawbacks of contrastive approaches are that they require a careful choice of positive and negative pairs [79] and that they often rely on large number of such negatives, inducing a high computational cost [17]. Alternatives to the contrastive approach, such as clustering and regression, avoid the need and cost of multiple negatives. Clustering-based methods [5, 8, 11, 13, 14, 38, 77, 84] alternate between learning representations using clusters as targets, and clustering using the current representations (either online or offline). Most related to our work are regression-based methods that instead try to directly regress a representation extracted from a different view of the image [27, 68]. **BraVe** is directly inspired from [29] but the views come from different modalities and augmentations, are processed by dedicated backbones and regress each other.

Video-based self-supervised learning. In the video domain, the pretext tasks for self-supervision have included predicting the future in pixel space by minimising an MSE loss [62, 74, 81] or adversarial losses [52, 80]. However, the predictions of these models are usually blurred and cannot go beyond predicting short clips into the future. To avoid these difficulties, other works focus on learning representations in a more abstract space, by using pretext tasks that predict the temporal order of video frames [56] or the arrow of time [83]. In this direction also, video contrastive methods have been very successful [18, 31, 32, 67]. In addition to data augmentations used for images, these works use temporal cues to build *positive pairs*. Yet the costs of training such systems are significant and complex hard-negative mining strategies are needed to improve the training efficiency [22]. Concurrent to our work, [23] introduces ρBYOL which consists in directly applying BYOL, an image self-supervised technique, to video. Although ρBYOL circumvents the use of negatives, it still requires an EMA (Exponential Moving Average) network to generate the targets, increasing the computational complexity. Our method avoids this computational overhead while obtaining state-of-the-art performance on popular video benchmarks. Furthermore, our approach may leverage predictive tasks, such as predicting other crops in the video or optical flow, reminiscent of earlier predictive work [74, 82]; but predicting in a learned feature space by building on a more recent self-supervised approach [29].

Audio-video self-supervised learning. Video and audio have been used as a rich source of self-supervision [5, 6, 7, 45, 57, 60, 63, 70]. A simple but effective approach to train representations consists in classifying whether a video clip and an audio sample correspond to each other [6, 7, 45, 60, 70]. Some works propose to use language obtained from speech recognition as an additional supervisory signal [3,

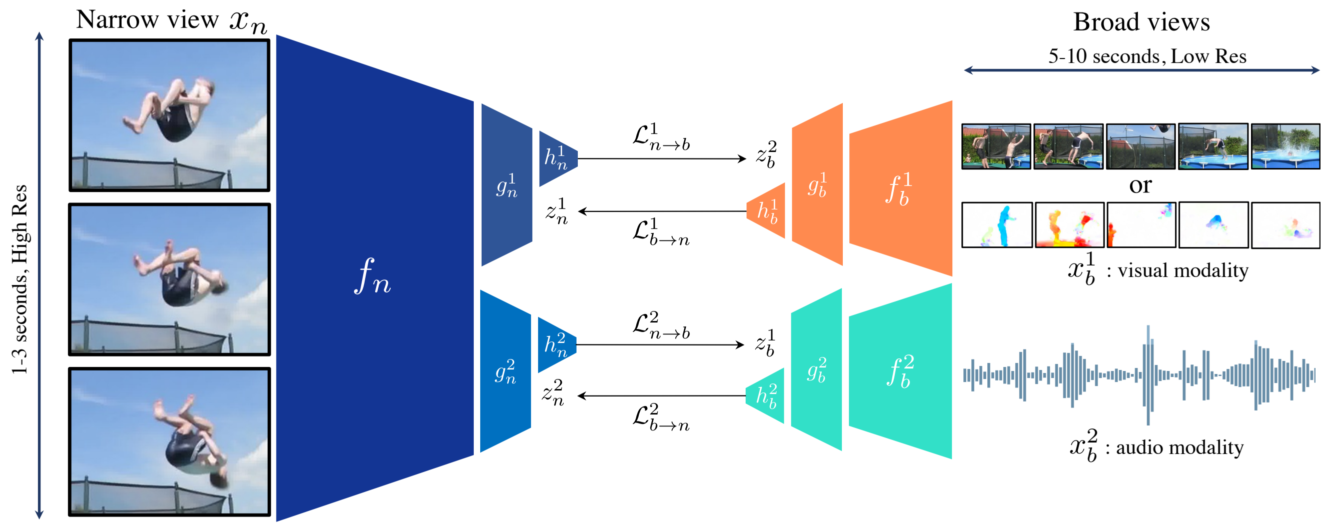

Figure 2. **BraVe**. Given a narrow view x_n spanning a few seconds at high resolution and broad views x_b^1 and x_b^2 covering a larger temporal extent in the video for different modalities, we train independent networks running on the narrow and the broad views to mutually regress each other. This is done by defining two regression losses: $\mathcal{L}_{n\to b}$ to predict a broad view from the narrow view, and $\mathcal{L}_{b\to n}$ enforcing the other way around. To avoid collapse of the learned representations, we introduce three stages of processing as previously done in BYOL [29]: backbone networks (f_n for the narrow view and f_b^1, f_b^2 for the broad views), projector networks (g_n and g_b^1, g_b^2) and predictor networks (h_n and h_b^1, h_b^2). For the broad views, we consider both visual modalities (RGB frames or optical flow) and audio modality.

4, 51, 53, 54, 69, 71, 76]. Related to ours, recent work finds that distilling flow and audio into a RGB encoder leads to strong representations [66], using an evolutionary search algorithm on the loss function. In contrast with this approach, our framework does not require to define modality-specific losses, is simpler to train (no need to balance the losses), and obtains better performance across the board.

3. Broaden Your Views for Self-Supervised Video Learning

In this section, we detail our approach dubbed **BraVe** for learning self-supervised state-of-the-art representations from a large set of videos, as measured by performance when transferring to downstream tasks. **BraVe**, illustrated in Figure 2, learns by direct regression from a high resolution narrow view that only spans a short clip to a lower resolution broader view which covers a larger temporal context of the video. Multiple options can be considered for the broad view: it can either come from the same modality as the narrow view (RGB in our case) or a different one such as flow or audio. Multiple views can also be combined to further improve performance. Next, we formally describe the learning framework in Section 3.1 and provide intuition why this may be a good self-supervised objective. Then, in Section 3.2, we describe the components and views we use in practice in two standard settings: learning from (i) visual signals alone, and from (ii) visual and audio modalities.

3.1. The BraVe learning framework

General overview. Given a video x that can be composed of multiple modalities, we randomly extract two complementary views: a narrow view x_n that spans a short timeframe in the video (around 1-3 seconds) and a broad view x_b that covers a larger extent of the video (around 5-10 seconds). Details on how these views are obtained are given in Section 3.2. By introducing this temporal asymmetry in the creation of the views, the proposed task consists in extrapolating the full context of the video (the broad view) from only a small portion of the video (the narrow view) as illustrated in Figure 1. We hypothesize that to solve this task, good representations must be learned, which can then be useful for semantic downstream tasks. More formally, we train networks to minimize the training loss $\mathcal{L}$ defined for a given video x as follows:

$$\mathcal{L}(x) = \underbrace{\mathcal{L}_{n\to b}(x)}_{\text{Narrow}\to\text{Broad}} + \underbrace{\mathcal{L}_{b\to n}(x)}_{\text{Broad}\to\text{Narrow}} . \quad (1)$$

This loss is composed of two terms: (i) a prediction loss from the narrow to the broad view, and (ii) a complementary loss to regress the narrow view from the broad view.

BraVe: losses and architectures. For simplicity and computational purposes, we opt for simple regression losses for $\mathcal{L}_{n\to b}$ and $\mathcal{L}_{b\to n}$. This is indeed simpler than standard contrastive losses that require large batches and therefore high compute to work well [17]. One challenge however, is the risk of collapse, since a trivial solution could be to always predict a constant which would lead to perfect regression losses across views. To avoid this, we draw inspiration from recent work [29, 30] in the way we design our networks and losses, as detailed next.

As illustrated in Figure 2, we first define a backbone network f_n whose role is to extract a representation from the narrow view x_n. Similarly, we define a backbone network f_b acting on the broad view x_b. Note that in our framework, the parameters and even the underlying architectures of f_n and f_b can differ since they act on views of a different nature. These representations are then respectively transformed by projectors g_n and g_b, projecting $f_n(x_n)$ and $f_b(x_b)$ to yield the narrow embedding $z_n = g_n(f_n(x_n))$ and the broad one $z_b = g_b(f_b(x_b))$. Inspired by [29], we then define a third stage of processing called the narrow view predictor h_n that takes the projected embedding from the narrow view z_n and produces a prediction $h_n(z_n)$ that is used to regress the broad view z_b using the following loss:

$$\mathcal{L}_{n\to b}(x) = \left\| \frac{h_n(z_n)}{\|h_n(z_n)\|_2} - \texttt{sg}\left[\frac{z_b}{\|z_b\|_2}\right] \right\|_2^2, \qquad (2)$$

where $\texttt{sg}[\cdot]$ denotes the "stop gradient" operator, which operates on its input as the identity, but has zero partial derivatives. Since the loss $\mathcal{L}_{n\to b}$ only depends on the networks associated with the narrow view, we also define a loss to provide training signal for the broad view network. To that end, we introduce a broad view predictor h_b that takes the projected embedding from the broad view z_b and produces a prediction $h_b(z_b)$ that is used to regress the narrow view embedding z_n using the following loss:

$$\mathcal{L}_{b\to n}(x) = \left\| \frac{h_b(z_b)}{\|h_b(z_b)\|_2} - \texttt{sg}\left[\frac{z_n}{\|z_n\|_2}\right] \right\|_2^2. \qquad (3)$$

The role of these predictors is crucial to avoid collapse as found in [29], which we confirm experimentally. The same is true for the stop gradient operator. Differently from [29], we do not use exponential moving averages (EMA) on the weights of the network that process the view being regressed. Unlike [23, 29], who required the moving average for improved performance, we find that this is not necessary in our case.

Intuitions about what needs to be learned by `BraVe`. While the proposed approach avoids plain collapse of the representations, it is also important to question what needs to be learned in order for the loss (1) to be optimized. In particular, we want the narrow backbone to learn to predict the full context represented by the broad view. However, one challenge is to prevent the broad backbone from instead simply learning to throw the broad information away and only keeping the signal contained in the narrow view. To avoid this, we sample the narrow and broad views independently in time when they come from the same visual modality so that it is difficult for the broad backbone to predict what the narrow view is going to be. By doing so, we argue that the best solution to solve the task is for the narrow backbone to extrapolate what is happening in the broad view. We empirically verify the importance of this independent sampling in our experiments in section 4.

Dealing with multiple views from one modality. `BraVe` can be extended to handle K broad views (with $K > 1$) coming from the same modality. To do so, we keep a single backbone f_b, projector g_b and predictor h_b for all broad views. For each broad view x_b^k, we individually compute the projection $z_b^k = f_b(x_b^k)$ and the projection $h_b(z_b^k)$. The target for the narrow backbone used in $\mathcal{L}_{n\to b}$ (2) is obtained by averaging these broad views projections: $z_b = \frac{1}{K}\sum z_b^k$. To compute the $\mathcal{L}_{b\to n}$ loss, we average the individual losses $\mathcal{L}_{b\to n}^k$ of the different predictions $h_b(z_b^k)$:

$$\mathcal{L}_{b\to n}^k(x) = \left\| \frac{h_b(z_b^k)}{\|h_b(z_b^k)\|_2} - \texttt{sg}\left[\frac{z_n}{\|z_n\|_2}\right] \right\|_2^2. \qquad (4)$$

Dealing with multiple views from different modalities. **`BraVe`** can also be extended to handle K broad views (with $K > 1$) coming from different modalities. To do so and as illustrated in Figure 2, we keep a single narrow backbone network f_n but introduce specific narrow projectors and predictors for each broad views: $\{(g_n^1, h_n^1), \cdots, (g_n^K, h_n^K)\}$. Each additional broad view x_b^k has its own set of backbone, projector and predictor : f_b^k, g_b^k and h_b^k, respectively. Given this, all regression losses are simply aggregated over all pairs composed by the narrow view x_n and the different broad views $\{x_b^k\}_k$:

$$\mathcal{L}(x) = \sum_{k=1}^{K} \mathcal{L}_{n\to b}^k(x) + \mathcal{L}_{b\to n}^k(x). \qquad (5)$$

When using different modalities, the risk for the broad network to only focus on the narrow view is reduced due to the modality gap between the two views. Furthermore, when using audio, syncing helps slightly as previously observed in visual-audio work [45]. We analyse further the audio-visual syncing strategies in the extended paper [1].

Final loss. Given a large set of videos $\{x^i\}_{i=1}^N$, we train our model to minimize:

$$\min_{\substack{f_n,g_n,h_n\\ f_b,g_b,h_b}} \sum_{i=1}^{N} \mathcal{L}(x^i). \qquad (6)$$

Next, we provide more details on the specific components that are used when **`BraVe`** is applied in the unimodal setting and the multimodal setting; as well as how the narrow and broad views are constructed in each case.

3.2. Broad views from visual and audio modalities

In our framework, we regress the representation of a broad backbone which sees a larger context of the video. The broad view is meant to provide information about the full video clip including more temporal context, in order to supervise the narrow backbone f_n. As the different views are processed by different backbones, we can apply a different set of pre-processing and augmentation functions to any of the views. In this section, we first describe the set of transformations that we use when training with visual inputs alone, and then when training with both visual and audio inputs.

Visual modalities. When sampling the broad view from the visual modalities, we aim to cover a large temporal context, the full clip. Accessing more temporal context typically means increasing the number of frames, and thus introducing extra computational complexity. To avoid this overhead, we decrease the spatial resolution of the broad view in order to keep the number of pixels constant. In Section 4 we show the effectiveness of trading temporal context for spatial resolution in the broad view. By keeping the computational cost fixed, we ensure that our method is computationally competitive with alternative self-supervised approaches.

Additionally to the temporal sampling, the set of transformations we consider for use on the narrow and broad views are motivated from two complementary perspectives. First, we can design the transformations $\mathcal{T}_b$ used for the broad view to extract specific features from the input modality, sought to enrich the learned representations $f_n(x_n)$ with a certain type of information. Second, similarly to the use of augmentations in a wide number of machine learning approaches, and in particular in contrastive and regression-based self-supervised learning approaches, we also employ such stochastic transformations to enforce invariance or equivariance constraints on the learned representations. In contrast to the use of augmentations in these self-supervised frameworks however, we emphasize that we do not impose that the set of transformations $\mathcal{T}_n$ used on the narrow view be the same as the set of transformations $\mathcal{T}_b$ used on the broad views. To explore this, we employ a recently introduced augmentation procedure relying on random convolutions [86], by which we augment only the broad view. Details about the random convolutions can be found in the extended paper [1].

Alternatively, we can use optical flow as substitute of RGB in the broad view, which is reminiscent of [75], where the flow network is used to teach the RGB network. Optical flow from sequential images can provide supervision to emphasize motion in the learned representations extracted from the source, which has shown to be important for predicting actions [32, 72, 82]. Optical flow can be extracted using an off-the-shelf unsupervised flow extraction algorithm. As flow is computed once for the full dataset, its computational overhead is negligible compared to training time.

Audio modalities. Our framework can leverage audio as supervisory signal in the broad view. We can either use a single audio broad view or combine a visual broad view and an audio broad view for stronger self-supervision. Audio is a strong supervisory signal, and has been extensively used for self-supervision in videos as it strongly correlates with the visual content, while being easier to process computationally. As pre-processing, we extract spectrograms from consecutive short-time windows on the waveform using Fourier transforms. This approach has been shown to be very effective in obtaining state-of-the-art performance on supervised [24, 44] and unsupervised [4, 40, 41] approaches. For this reason, we encode the audio using a log-mel spectrogram representation as $x_b \in \mathbb{R}^{T_s \times D}$ where T_s is the number of spectrogram frames and D denotes the number of features. Similar to the unimodal setting, we experiment with enlarging the temporal window for the extraction of the audio view, compared with the temporal window of the narrow video view, seeking to increase the amount of context information present in the supervisory signal. Finally, as explained in the previous section, we make sure that the visual narrow view and the audio broad view are in sync at their starting point.

4. Experiments

In this section, we evaluate **`BraVe`** and compare its performance against relevant state-of-the-art methods trained on similar data and modalities.

4.1. Experimental setting

Video-only experiments. In the video-only setting, unless stated otherwise we conduct our experiments on the Kinetics-600 dataset [15]. The dataset has 600 action classes and contains 447k videos at the time of submission, 362k in the train set. We also train on the Kinetics-400 [42] dataset for comparison with the state-of-the-art.

Audio-video experiments. In the crossmodal training setting, we use the AudioSet [25] as pre-training dataset. The dataset has 527 action classes and contains 1.9M videos in the training set at the time of submission.

Architectures. For spatiotemporal volumes such as the sequences of RGB or flow frames, unless specified otherwise, we use the TSM-ResNet50 (TSM-50) [49] architecture for the narrow backbone. For the broad visual backbone we always use a TSM-50 backbone. Video inputs are sampled at 12.5 frames per second (FPS), except when using the R3D architecture which we train sampling videos at 6.25 FPS. Unless stated otherwise, we train the narrow backbone on inputs of 16 frames (1.3 seconds) at resolution 224×224, and the broad backbone on inputs of 64 frames at 6.25 FPS (10s) at resolution 112×112. To see how our method scales to different and bigger architectures, we also experiment with different backbones for the narrow network with the R3D architecture (as described in [23]) and TSM with twice the number of channels in each layer (TSM-50x2). We use these networks only for the narrow view and always use TSM-50 in the broad view. For the broad backbone processing log-mel spectrograms, we use ResNet-50 [35]. All models are trained using a two-layer MLP for the projector and predictor heads with a hidden layer of dimension 4096. We use batch normalization after each hidden layer. In the projector heads, we use batch normalisation after the last layer. We use 128 as the output dimension of projectors and predictors.

Feature extraction. For flow extraction, we use the TV-L1 [88] algorithm. We use 80 bins for extracting log-mel spectrograms.

Augmentations. We sample and augment all the visual views independently. For any narrow view, we uniformly sample a temporal offset between 0 and $T - \tau_n$, where T is the duration of the video clip and τ_n denotes the length of the narrow view. We extract the view starting at this offset. For the broad view, we randomly sample the offset between 0 and T. We pad any broad view of insufficient length with a clip extracted from the start of the video sample (*i.e.* looping over the sequence). For all visual modalities (including the flow), we use random cropping and horizontal flipping. For the RGB views, we additionally employ Gaussian blurring as well as scale and color jittering. We also explore the use of random convolutions as an augmentation procedure. Following [48], we use He initialization [34] for the weights and fixed zero bias, sampling the size of the kernel uniformly across odd values ranging from 1 to 11. For audio, we use the same starting point as the narrow view, but extend it for a longer time window. If necessary, similarly to the RGB case, we pad the broad audio view with audio extracted from the start of the audio clip. See extended paper [1] for details.

Self-supervised training details. We discard labels at training time, and only use them for downstream evaluation. We employ a batch size of 512 and train for 300k steps, setting the initial learning rate to 4.8 for models without audio and 1.0 for models with audio. We train all models using LARS [87]. We use 5000 warm up steps and cosine learning rate schedule [50]. Following BYOL [29], we multiply the learning rate for all predictors (h_n and h_b) by 10. For batch norm layers, we use a decay rate of 0.9 and epsilon of 1e-5. We use weight-decay of 0.01. As in [23], we do not apply LARS and weight decay to the biases and batch norm parameters. More details are given in the extended paper [1].

4.2. Downstream tasks

We use two standard settings to evaluate the quality of the learned visual representations from the narrow backbone f_n: in the *linear* setting, we train a linear layer over frozen features extracted by f_n; in the *fine-tuning* setting, we train f_n and the classifier head end-to-end. Unless stated otherwise, we use 32 frames for video evaluation, to be comparable to previous work. We evaluate video representations using the HMDB51 dataset [46], the UCF101 dataset [73] and the Kinetics-600 [16] validation set. The HMBD51 dataset contains 5K videos, corresponding to 51 classes. The UCF101 dataset contains 13K videos, corresponding to 101 classes. The Kinetics-600 validation set contains 28k videos. We also evaluate the learned audio representations from the corresponding broad backbone, f_b, on both the test set of the AudioSet dataset (20K samples, 527 classes) as well as the smaller ESC-50 dataset [65] (2K samples, 50 classes). Following standard procedure, we report top-1 accuracy for all datasets except for Audioset where we report the mean average precision [40]. For the datasets that have official splits (3 for UCF101/HMDB51 and 5 for ESC-50), we follow the standard procedure where split#1 serves as the validation set and the average accuracy over all splits is then reported.

Table 1. **Importance of the broad view.** We evaluate the impact of the temporal extent of the narrow (τ_n) and broad (τ_b) views. M_b is the modality used in the broad view. RC stands for random convolutions. K600 stands for Kinetics-600 and AS for AudioSet.

Dataset	M_b	τ_n	τ_b	HMDB51	UCF101	K600
K600	RGB+RC	10s	10s	58.7	80.0	47.4
K600	RGB+RC	1.3s	1.3s	59.4	88.1	66.3
K600	RGB+RC	1.3s	5s	61.4	88.9	65.1
K600	RGB+RC	1.3s	10s	**65.1**	**90.0**	**67.4**
AS	Audio	1.3s	1.3s	**68.3**	92.2	69.0
AS	Audio	1.3s	5s	67.5	92.4	69.9
AS	Audio	1.3s	10s	67.3	**92.6**	**70.3**

Linear setting. For HMDB51, UCF101 and ESC-50, we extract representations from 10 epochs worth of augmented samples using the learned narrow backbone, and we train a linear SVM using scikit-learn [64] on these frozen features. For Kinetics-600 and AudioSet which are larger, we instead train the linear classifier using the LARS [87] optimiser for K600 and the Adam optimizer [43] for AS. In all cases, we use the same augmentations as during unsupervised pretraining except for gaussian blur. Full details are provided in the extended paper [1]. At test time, we average the prediction over 30 clips (10 temporal clips each with 3 spatial crops) as done in [67]. For AudioSet, we follow [40] and use a fully-connected classifier, with one hidden layer of 512 units, in place of the linear classifier.

Fine-tuning setting. In this setting, we add a single, randomly initialized, linear layer at the output of the narrow backbone. We initialize the narrow backbone's weights with those learned using **`BraVe`**, and we fine-tune this architecture end-to-end. Following previous work, we perform this evaluation on the HMDB51 and UCF101 datasets. We use a similar test time procedure as for the linear setting. Details are given in the extended paper [1].

4.3. Ablation study

In this section, we study the effect of the different components of **`BraVe`** on the performance of the narrow backbone f_n. Specifically, we study four main elements: **(i)** the effect

Table 2. **Visual transformation for the broad view.** We compare various augmentations for the visual input of the broad view, when pre-training on Kinetics-600. We use $\tau_n = 1.3s$ (narrow extent) and $\tau_b = 10s$ (broad extent). RC stands for random convolutions.

M_b	HMDB51	UCF101	K600
RGB	61.3	89.9	**67.7**
RGB+RC	65.1	90.0	67.4
Flow	**65.6**	**91.1**	65.8

Table 3. **Number of broad views.** Effect of adding multiple broad views of the same modality (RGB+RC).

Dataset	Number of views	HMDB51	UCF101	K600
K600	1	65.1	90.0	67.4
K600	2	**65.6**	**91.7**	69.1
K600	3	65.2	91.5	**69.5**

Table 4. **Sync views.** Effect of syncing the narrow and broad views.

Dataset	Sync	M_b	HMDB51	UCF101	K600
K600	✗	RGB+RC	**65.1**	**90.0**	**67.4**
K600	✓	RGB+RC	64.2	86.2	59.9

of the temporal extents of the narrow and broad views, **(ii)** the improvements brought by different choices of transformations for the visual modality, **(iii)** the improvements resulting from using multiple broad views of the same modality and **(iv)** the effect of temporally syncing the narrow view and the broad view. By default, we conduct this analysis using the HMDB51, UCF101 and K600 benchmarks in the linear setting. Further discussion on sharing weights across backbones, evaluating the broad backbone or using **`BraVe`** to train image models can be found in the extended paper [1].

Importance of the broad view. We study the effect of the temporal extent of the narrow and broad views in the RGB-only setting (using random convolutions RGB+RC for the broad view) and the multimodal setting (using audio spectrogram for the broad view). We report results in Table 1. First, in the unimodal setting, we find that for a narrow view extent τ_n of $1.3s$, performance improves significantly across the two downstream tasks as we increase the duration of the broad view τ_b from $1.3s$ to $10s$, (*e.g.* from 59.4 to 65.1 on HMDB51). This empirically supports our intuition that broader views can provide better supervision. Second, we find that using temporally large views of $10s$ for both the narrow view and the broad view degrades performance, as the task becomes significantly easier and we are unlikely to get rich embeddings. In the multimodal setting, we find that increasing the context from $1.3s$ to $5s$ brings an improvement to UCF101 and specially K600, although it is smaller than in the visual setting. As the performance when extending the broad view to $10s$ is comparable with using $5s$, we use the less expensive $5s$ for the audio broad view.

Visual transformation for the broad view. In Table 2, we investigate the effect of using different visual inputs in the broad view. First, we see that using Random Convolutions (RC) [86] on the RGB frames significantly improves performance, compared to using standard RGB frames. **`BraVe`** enables the use of such an aggressive augmentation since it has a dedicated backbone for that view. Moreover, only using this augmentation on the broad view ensures that the backbone trained on the narrow view does not suffer from shift in distribution of intensities [86]. Furthermore, using optical flow for the broad view leads to further improvement in HMDB51 and UCF101 when compared to using RC augmentation. This demonstrates a surprisingly high effectiveness of leveraging hand-designed features, probably because this allows important factors – here motion and segmentation information – to be included in the representation.

Number of broad views. In Table 3, we study the impact of having more than one broad view of the same modality. Adding additional broad views results in improved performance on UCF-101 and Kinetics. We believe that using multiple views serves as augmentation for **`BraVe`**, which regresses to the average of multiple projection and this is likely to be more representative of the full video.

Syncing views. In Table 4, we study the effect of having the same temporal starting point for the narrow and the broad view. As expected, when using a broad visual modality, syncing significantly decreases performance. We hypothesise that when both views are in sync, the broad network can simply focus its prediction only on the narrow view since the relative position of the views is deterministic hence making the self-supervised task easier as explained in Section 3.1.

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

We compare **`BraVe`** against the state-of-the-art for self-supervised video representation learning in Table 5. Note that when evaluating in visual tasks, we only use the RGB modality to be comparable to previous work.

Visual only on Kinetics. In the setting where we use only the video modality combined with three broad views using random convolutions, we find that **`BraVe`** outperforms the CVRL approach [67] on UCF101 and HMDB both linear and fine-tuning under similar conditions (R3D and K600). Furthermore, when integrating the flow modality in the broad view and using similar backbone (R3D) and dataset (K400), **`BraVe`** perfoms not far ($< 1\%$) from ρ-BYOL [23]. Note that differently from [23], our method does not require an EMA network, which introduces additional computational requirements. Finally, we observe that using the flow modality increases the performance for all the architectures.

Multimodal on AudioSet. We also compare our approach

Table 5. **Comparison of learnt representations against the state-of-the-art.** We report the performance in the linear and fine-tuning (FT) settings, on three vision benchmarks: UCF101, HMDB51, Kinetics-600 (K600); as well as on two audio benchmarks: ESC-50 and AudioSet (AS). K400 is Kinetics-400, YT8M is Youtube-8M [2], IG65M is Instagram-65M [26]. We specify dataset sizes in years. We denote the modalities $\mathcal{M}$ used for training by: V for RGB, F for flow and A for audio. **All models use only RGB for the visual downstream tasks.**

					UCF101		HMDB51		K600	ESC-50	AS
Method	Backbone (#params)	Dataset	Years	$\mathcal{M}$	Linear	FT	Linear	FT	Linear	Linear	MLP
CoCLR [32]	S3D (9.1M)	K400	0.07	VF	74.5	87.9	46.1	54.6		/	/
CVRL [67]	R3D50 (31.8M)	K600	0.1	V	90.6	93.4	59.7	68.0	**70.4**	/	/
ρBYOL [23]	R3D50 (31.8M)	K400	0.07	V		95.5		73.6		/	/
ρBYOL [23]	S3D (9.1M)	K400	0.07	V		**96.3**		**75.0**		/	/
BraVe:V↔V×3 (ours)	R3D50 (31.8M)	K400	0.07	V	90.6	93.7	65.1	72.0	66.5	/	/
BraVe:V↔F×3 (ours)	R3D50 (31.8M)	K400	0.07	VF	92.0	94.7	67.5	72.7	66.7	/	/
BraVe:V↔V×3 (ours)	TSM-50 (23.5M)	K600	0.1	V	91.6	94.1	65.2	73.1	69.5	/	/
BraVe:V↔F×3 (ours)	TSM-50 (23.5M)	K600	0.1	VF	91.9	94.7	65.7	74.0	67.1	/	/
BraVe:V↔V×3 (ours)	R3D50 (31.8M)	K600	0.1	V	91.9	94.4	67.6	73.9	69.1	/	/
BraVe:V↔F×3 (ours)	R3D50 (31.8M)	K600	0.1	VF	**92.7**	95.1	**68.9**	74.3	68.1	/	/
ELo [66]	R(2+1)D-50 (46.9M)	YT8M	13	VFA		93.8	64.5	67.4			
AVID [57]	R(2+1)D-50 (46.9M)	AS	1	VA		91.5		64.7		89.2	
GDT [63]	R(2+1)D-18 (33.3M)	AS	1	VA		92.5		66.1		88.5	
MMV [4]	R(2+1)D-18 (33.3M)	AS	1	VA	83.9	91.5	60.0	70.1	55.5	85.6	29.7
XDC [5]	R(2+1)D-18 (33.3M)	AS	1	VA		93.0		63.7		84.8	
XDC [5]	R(2+1)D-18 (33.3M)	IG65M	21	VA		95.5		68.9		85.4	
BraVe:V↔A (ours)	TSM-50 (23.5M)	AS	1	VA	**93.4**	95.6	69.1	75.3	**71.1**	92.1	**36.4**
BraVe:V↔FA (ours)	TSM-50 (23.5M)	AS	1	VFA	93.2	95.8	70.2	76.9	70.3	92.6	36.3
BraVe:V↔FA (ours)	TSM-50x2 (93.9M)	AS	1	VFA	92.8	**96.5**	**70.6**	**79.3**	70.5	**92.9**	**36.4**
Supervised [12, 44, 66, 85]						96.8	71.5	75.9	82.4	94.7	43.9

in the multimodal (visual and audio modalities) setting by training **BraVe** on AudioSet. In that setting, we train for 620k steps instead of 300k, as AudioSet is significantly larger than Kinetics-600. We increase the number of input frames of the narrow network from 16 to 32 frames (at 12.5FPS). We use $\tau_b = 5s$ for the audio broad view. We make four important observations. **(i)** Under this setting, **BraVe** outperforms all state-of-the-art methods when using the same pretraining data and similar backbone. In particular, when using TSM we outperform the current state-of-the-art XDC [5] and MMV [4] which uses a network with more parameters. **(ii)** Interestingly, we observe that using two broad views coming from two different modalities, audio and flow, benefits performance on HMDB51 (+1.6%) but performs similarly in UCF101 (+0.2%). **(iii)** **BraVe** benefits from using larger visual backbones. When using the larger backbone TSM-50x2 (93.9M parameters), **BraVe** establishes a new state-of-the-art on HMDB51 finetuning with 79.3 and UCF finetuning with 96.5. In HMDB51, it outperforms the best supervised results published to date (75.9 from [85]). **(iv)** When evaluating the performance of the broad audio network we also significantly outperform previous state-of-the-art on two challenging benchmarks, ESC-50 and Audioset. Notably, we significantly improve the performance in AudioSet, the hardest of the audio tasks.

5. Conclusion

In this paper, we introduced **BraVe**, a self-supervised learning framework for video. Our method efficiently learns its representation by supervising a temporally narrow view with a general broad view, which can be either computed from RGB, flow or audio. Our model achieves state-of-the-art performance when trained on datasets such as Kinetics or AudioSet. Notably, when trained with a larger backbone, **BraVe** outperforms the previous best supervised transfer result on the challenging HMDB51 benchmark.

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