iBoot: Image-bootstrapped Self-Supervised Video Representation Learning

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Abstract

Learning visual representations through self-supervision is an extremely challenging task as the network needs to sieve relevant patterns from spurious distractors without the active guidance provided by supervision. This is achieved through heavy data augmentation, large-scale datasets and prohibitive amounts of compute. *Video* self-supervised learning (SSL) suffers from added challenges: video datasets are typically not as large as image datasets, compute is an order of magnitude larger, and the amount of spurious patterns the optimizer has to sieve through is multiplied several fold. Thus, directly learning self-supervised representations from video data might result in sub-optimal performance. To address this, we propose to utilize a strong image-based model, pre-trained with self- or language supervision, in a video representation learning framework, enabling the model to learn strong spatial and temporal information without relying on the video labeled data. To this end, we modify the typical video-based SSL design and objective to encourage the video encoder to *subsume* the semantic content of an image-based model trained on a general domain. The proposed algorithm is shown to learn much more efficiently (i.e. in less epochs and with a smaller batch) and results in a new state-of-the-art performance on standard downstream tasks among single-modality SSL methods.

1 Introduction

Self-supervised learning (SSL) is the task of learning representations directly from data without the need of manually-defined annotations. SSL has very recently gained widespread attention due to a series of transformative developments [10, 11, 12] that have turned SSL into a key technology on a wide range of computer vision applications. SSL can be used as a pre-training step, often resulting in improved performance on downstream tasks compared to that of pre-training with a fully-supervised method. Furthermore, SSL has been shown to be a key component for few-shot applications [14, 20, 52], zero-shot generalization [62], and semi-supervised learning [68] among others.

Despite the fast progress in image-based SSL [8, 12, 24, 26], its success has not yet been fully matched by video-based SSL techniques. For example, in video-based problems, downstream performance when fine-tuning from an SSL pre-trained model trails behind fine-tunning from a pre-trained model learned through standard supervision. This is likely due to the extra challenges introduced by videos, to wit, much higher optimization costs, higher data dimensionality, and smaller dataset sizes.

Recent video SSL methods typically extend the image SSL ones, both in the contrastive [48, 40] and non-contrastive (via consistency loss) settings [50]. Typically, these methods either sample different

temporal clips within a sequence and extend standard image augmentations to video to create the positive pairs, or extend into multiple modalities so as to integrate optical flow, audio, or text. For instance, a direct extension of BYOL [24] is the state-of-the-art for single-modality video SSL [19], with the only difference being on how to sample different views within a sequence.

In this work, we propose *iBoot*, the "Image-bootstrapped Video Representation Learning". We look into an aspect surprisingly overlooked by prior work, that is, image representation learning methods have learnt to represent images expressively and we argue one can skip re-doing this for learning spatial aspects of the video data. Therefore, we propose to learn a representation that rather than replacing it, expands on the frame representation. We achieve this by making sure the video encoder subsumes the frame representation provided by a strong image-based foundation model trained with self-supervision [8] or natural language supervision such as CLIP [49]. We empirically show that iBoot, which is fundamentally different in spirit compared to existing video SSL methods [19], performs better at a usually lower computational requirement.

More specifically, instead of using the widely adopted design wherein two streams of a network (online and target as in [19]) with the same architecture are trained, we utilize a strong pre-trained image foundation model to serve as the *target network*, guiding the online network (which can be a regular temporal model such as 3D-ResNet [18]) to learn a strong and expressive spatial representation throughout training. This happens in parallel to the online network's attempt to further learn the temporal persistency over multiple augmented clips of a sequence.

In summary, our contributions are as follows:
(1) We propose a simple yet highly effective approach for video SSL that benefits from strong image foundation models [8, 49] in a simple pipeline, outperforming existing video SSL methods on various downstream tasks. We show that our method converges much faster and can use a smaller batch size, enabling training with more widely-available and reasonable compute budgets. **(2)** We conduct a thorough exploration of key design aspects that lead to a well-performing realization of the proposed idea, including, among others, (a) various architectures (ResNet, ViT), and (b) various types of supervision (fully supervised on ImageNet, self-supervised (SwaV, DINO) and weakly supervised (CLIP)) for training the image-based model. (3) We show that our best trained model outperforms the state-of-the-art method of [19] on various downstream tasks, e.g., by 1.8% in linear evaluation and by 2.9% in semi-supervised classification (1% labels) on Kinetics-400 dataset.

2   Related Work

With the availability of huge amounts of unlabeled data, self-supervised representation learning has become an important technique, allowing machines to learn useful representation from such source of information. This leads to a general feature representation learning which benefits downstream visual recognition tasks. Great progress has been made towards visual SSL by focusing on discriminative approaches which treat visual representation learning in a similar fashion to supervised scenario, but where both the samples and labels are derived from an unlabeled data. A number of these methods rely on handcrafted pretext tasks such as image colorizing [35, 69] or inpainting [43] for image representation learning and spatio-temporal ordering [36, 41, 61, 65], tracking patches or pixels [58, 59], and predicting the playback speed [6] for video representation learning. Although effective to some extent, these approaches mostly rely on the heuristic design of auxiliary tasks which limit the generality of the learned representations.

An alternative to defining pretext tasks is to learn discriminative features based on contrastive learning in the latent space [10, 11, 12, 31]. To this end, a contranstive loss [55] is employed to learn how to pull together the positive pairs, coming from different views of the same image, and push apart the negative pairs, i.e., from different images. For example, SimCLR [10] constructs positives through different augmentations (views) of the same data example and negatives from other samples within a batch, and contrasts them in the latent space. Instead, MoCo [12] maintains a queue of negative samples and turns one branch into a momentum encoder to improve the consistency of the queue. Contrastive learning was shown to also be successful for video SSL [5, 25, 28, 29, 30, 37, 38, 48, 57].

Furthremore, compared to images, videos have other sources of information, such as audio and motion, which can provide contrastive approaches with a variety of modalities. In particular, a contrastive loss has been widely utilized for cross-modal discrimination of video from audio and/or optical flow [1, 2, 3, 33, 40, 42, 44, 47, 45, 46]. Adding other modalities besides a visual one has
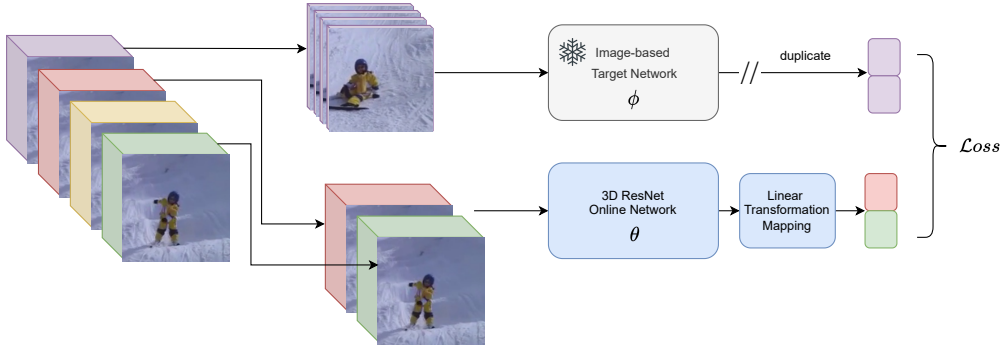
Figure 1: An overview of iBoot: during training, iBoot encourages the features of k clips computed by online network to be similar to the reference features computed by the frozen target network.

been of interest in recent years in the image domain as well. As an example, [49] utilizes natural language supervision for image representation learning.

Recent works have shown that visual representations can be learned without discriminating between samples and instead focus only on learning from views of the same sample [7, 8, 13, 24]. In particular, BYOL [24] and DINO [8] directly predict the output of one view from another view in a Siamese network in which one branch is a momentum encoder. Instead, SwAV [7] predicts cluster assignments of the representation of the opposite view, rather than the representation itself. Consistency loss has been also employed in video representation learning as in [19, 50]. In these approaches, in addition to image augmentations, different temporal clips within a sequence are sampled and used to build positive pairs, forcing a consistent representation across different video segments.

Recently, inspired by BERT [15], which was developed for masked language modeling, masked image modeling has been proposed for visual representation learning [4, 26, 70]. To this end, during pre-training, they randomly mask some proportion of image patches and feed the corrupted input to a Transformer model. The model learns to recover the visual tokens [4, 70] or pixels [26]. The pre-training task of masking and prediction has been recently used for video SSL as well, following a similar strategy of masking video blocks and aim to reconstruct either a HOG representation of the masked blocks [60], or in [53], discretized video tokens generated via an offline VQ-VAE [56].

Unlike the aforementioned methods, we take an alternative approach to efficiently learning video representations. In this work, we build our approach upon the motivation of leveraging strong pre-trained image SSL foundation models to help the video SSL model to better learn the spatial aspect of the videos. We note that learning video representations by means of leveraging image representations has been previously investigated [21]. In particular, [21] proposes to use one or several image models trained through supervision (e.g. ImageNet-1k, PlaceNet) to assist in learning a spatial-temporal representation. To this end, the image model is used to obtain a prediction for each of the frames, and the soft predictions are used to supervise the video encoder. However, unlike [21], we frame our method purely in the self-supervised learning realm, do so within a state-of-the-art modern SSL method, and use a methodology that induces temporally-aware representations rather than representations that only work well for spatially datasets.

3 Proposed Method

We develop our approach upon ρBYOL (the best performing method from the ones described in [19]) by extending it to work in synergy with a pre-trained image-based model, rather than in a purely video self-supervised manner (as proposed in [19]). ρBYOL utilizes two neural networks with the same architecture, the online and target networks, to learn the visual representation. The online network is defined by a set of weights θ and the target network's parameters θ_m are the exponential moving average of the online parameters θ. BYOL minimizes negative cosine similarity between the online and target representations, each taking as input two (spatially and temporally) augmented views (also refer to as clips) of the same video. In this work, the proposed iBoot extends ρBYOL by capitalizing on the benefits of strong image-based foundation models.

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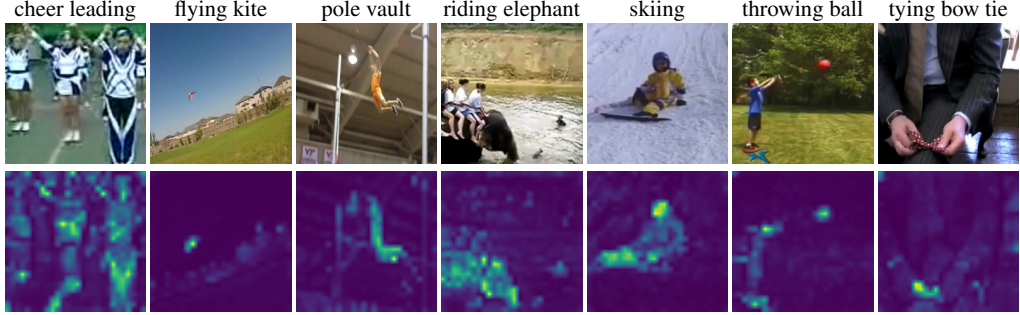| cheer leading | flying kite | pole vault | riding elephant | skiing | throwing ball | tying bow tie |

Figure 2: Attention maps of an ImageNet-1k pre-trained DINO model on Kinetics-400 frames. Although the model has not been trained or fine-tuned on any action/video dataset, it correctly attends to the relevant spatial information from the video.

More specifically, as illustrated in Figure 1, let an image-based pre-trained recognition model, parameterized with ϕ to denote our frozen target network. The online network, parameterized with θ, can be a standard video encoder such as 3D ResNet [18]. To train our model, we utilize different views, v_{ref}, v_1, and v_2, randomly sampled and augmented from a sequence. While v_{ref} acts as the input to the target network, we pass v_1 and v_2 to the online network. To obtain the reference features of the target network, we simply use the representations (framed-based or average pooled) produced by the pre-trained image-based model, for example the penultimate layer feature from ResNet or the output `[CLS]` token of the ViT. This way the image-based model can be utilized to provide a rich representation of the frames of the clip. Then, during training, we simply encourage the features of v_1 and v_2 produced by the online network to match that of the target one by minimizing the cosine distance loss,

$$\mathcal{L} = -\sum_{k \in \{k^+\}} \mathrm{sim}(q, k) = -\sum_{k \in \{k^+\}} 2 - 2 . \frac{\langle q , k \rangle}{\|q\|_2 . \|k\|_2} \tag{1}$$

where $q = f_\phi(v_{ref})$ is the features computed by the frozen target network and $k^+ \in W(f_\theta(v_i))$ for $i \in \{1, 2\}$ are the transformed features computed by the online network, wherein W is a linear transformation aiming to map the output dimension of the online network to that of the target one.

Given the above video representation learning setting, we explore the following directions for the image-based model: (a) *Different architectures:* we explore ResNet vs ViT models, and (b) *Different types of supervision:* we explore fully-supervised, self-supervised (i.e. SwAV [7], DINO[8]) and weakly-supervised (i.e. CLIP [49]) models.

One potential caveat is the relative domain gap between the image data it has been trained on and the video data it is applied to. As a sanity check, we empirically show that self-supervised models like DINO provide a general representation capable of capturing the semantic content of the frames in a video. Figure 2 illustrates the attention maps of a DINO-ViT (pre-trained on ImageNet-1k) on Kinetics-400 frames. As shown, these attentions maps correspond to coherent semantic regions of the actions of interest while the model has not been trained on any action dataset. This encourages us to perform the extensive exploration described in Sec. 4.3.

Remark. Although there have been great effort in avoiding the collapse phenomenon when pre-training SSL models in a non-contrastive setting, either through incorporating stop gradients [13], whitening [16], or other techniques [67], our approach suggests a simple yet effective way to handle the collapse by freezing the pre-trained target network. This alleviates the need for further tricks to avoid collapse since iBoot does not update the target network's parameters.

4 Experiments and Results

In this section, we describe the datasets, evaluation settings, and implementation details for pre-training and downstream tasks. We then present the results of an extensive set of ablation studies and finally compare our method to the state-of-the-art video SSL approaches.

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4.1 Pre-training

Datasets. Our self-supervised pre-training is done on Kinetics-400 [32](K400) which consists of ∼240k training and ∼20k validation video clips in 400 human action categories. In order to see the effect of using a larger-scale dataset during pre-training, we utilize the Kinetics-600 [9](K600) dataset which has ∼392k training videos and ∼30k validation videos in 600 classes. It is worth mentioning that we do not use any of these labels during the self-supervised pre-training.

Augmentation. For data augmentation during the self-supervised pre-training, we follow almost the same setting as in [19]. Given a full-length video, we randomly sample a clip ($T \times \tau$ frames), thus the input to the video encoder are T frames subsampled from the raw clip with a stride of τ where $T = \tau = 8$. Then, for each clip, we apply a consistent spatial augmentation on its frames as well. To this end, spatial cropping is done by randomly resizing the shorter spatial side of a video between [256,320] pixels and takes a random 224×224 crop extended over temporal dimension to extract a clip. To each clip, we apply a random horizontal flip, color distortion, and Gaussian blur following the recent self-supervised approaches [19, 48]. We use the color jittering with the probability of 0.8 and the color parameters {brightness, contrast, saturation, hue} = {0.2, 0.2, 0.2, 0.05}. We also apply random grayscaling with the probability of 0.2. For Gaussian blur we use a spatial kernel with standard-deviation $\in [0.1, 2.0]$ applied with a probability of 0.5.

Implementation details [1]**.** By default, we use a 3DResNet-50, 8×8 Slow pathway [18] as backbone. The input to the network are clips of $T = 8$ frames sampled with stride $\tau = 8$ from 64 raw-frames of video. We train the models with the LARS optimizer [66] for 100 epochs and a batch size of 104 (13×8) distributed over 8 V100 GPUs for the ablation studies. For the comparison to the state-of-the-art, we increase the number of training epochs to 200 and we use a batch size of 416 (13×32) distributed over 32 GPUs. Note that synchronized batch normalization across all GPUs is used during training. The learning rate is linearly ramped up during the first 8 epochs to its base value which is $lr = 2.4 \times \frac{bs}{256}$ using linear scaling rule [22] and then we decay the learning rate with a cosine scheduler [39]. The weight decay has been set to 10^{-6} during training. For the image-based models, we use the publicly released models such as DINO [8] and CLIP [49]. In particular, for the comparison to the state-of-the-art, we use the publicly released CLIP ViT-B/16 model [2]. This model has been pre-trained with the WIT dataset [49] containing about 400M image-text pairs.

4.2 Evaluation

In this section, we present the details of our evaluation protocols to evaluate our self-supervised video representation learning pipeline. Please note that, unless otherwise stated, for all the evaluation settings, we use clips of $T = 8$ frames sampled with stride $\tau = 8$ from 64 raw-frames of video.

Linear evaluation. Following existing methods [19, 27, 48, 50], we evaluate our approach by training a linear classifier on frozen features of K400 training set and report the top-1 classification accuracy on K400 validation set. In order to train the linear classifier, we use SGD as our optimizer with momentum set to 0.9. The learning rate starts from 0 and linearly increased during the first 8 epochs to its base value of 1.0 and then decay it with a cosine scheduler [39]. The model is trained with a mini-batch size of 64 for 100 epochs. During testing, we densely sample 10 clips from each video and apply a 3-crop evaluation following [19, 27, 48, 50].

Action classification. We report the fine-tuning accuracy on UCF101 [51], HMDB51 [34], and Something-Something V2 [23](SSv2) datasets. For UCF101 and HMDB51, we report results for the ablation studies using split1 for train/test split. We also report the averaged results over 3 splits of train/test for comparison to previous work, as in Table 10. For training the model on UCF101 and HMDB51, we use SGD with the momentum of 0.9 and an initial learning rate of 0.0025. The models are trained with a mini-batch size of 128 for 196 epochs. During testing, we densely sample 10 clips from each video and apply a 3-crop evaluation following [19, 27, 48, 50]. SSv2 dataset contains about 168k training videos and 24k validation videos in 174 video categories. What makes this dataset different from UCF101 or HMDB51 is the fact that many action categories in this dataset shares very similar background and object appearance, thus learning temporal information is crucial for the model to classify different actions. For training, we use SGD with the momentum of 0.9 and

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[1] iBoot is implemented upon PySlowFast [17].
[2] Available at `https://github.com/openai/CLIP`.

weight decay of 10^{-4}. The learning rate starts from 0.08 and linearly ramped up during the first 3 epochs to its base value of 0.15. Then we decay the learning rate with a cosine scheduler [39]. The models are trained with a mini-batch size of 64 for 40 epochs. During testing, unless otherwise stated, we follow [19] and sample 1 clip from each video and apply a 1-crop evaluation.

k**-Nearest Neighbor evaluation.** Since both training a linear classifier on frozen features or fine-tuning the features are sensitive to hyperparameters, inspired by [8, 63], we also evaluate the quality of features with a weighted nearest neighbor classifier (k-NN) and report top-1 classification accuracy on the validation set of K400. In particular, we use the frozen features of the pre-trained model computed from the training set of K400. The nearest neighbor classifier then matches the feature of a clip from the validation set to the k nearest stored features that vote for the label. Following [8] we use $k = 20$. This is a relatively fast and fair evaluation protocol as it does not rely on any hyperparameter tuning and the evaluation can be done with a single forward pass over the downstream dataset.

Semi-supervised learning. To further evaluate the video representations and compare it with the state-of-the-art approaches, we conduct semi-supervised learning experiments, i.e., fine-tuning the pre-trained network on small subsets of K400. Following [48], we sample 1% and 10% videos from each class in the training set. The settings are similar to the linear evaluation, except that the initial learning rate is 0.01. We evaluate this experiment on the original K400 validation set.

4.3 Ablation Studies

For the ablation studies, for UCF101 and HMDB51, we report top-1 classification accuracy using split1 for train/test split. We also report the top-1 classification accuracy of a k-NN classifier on the K400 dataset for different settings. Please note that unless otherwise stated, all the video SSL training in the ablation studies have been done on a single machine with 8 V100 GPUs for 100 epochs.

Effect of image-based pre-training with different level of supervision. As discussed in Section 3, iBoot utilizes the strong image-based pre-trained models to better learn semantic representations of the video frames. In Table 1, we compare a model that has been trained with two branches of video encoder, ρBYOL (the spatio-temporal extension of [24]), with those that utilize the pre-trained image-based models as the target network. In ρBYOL, as in [19], the target network's parameters θ_m are the exponential moving average of the online parameters θ. As clearly shown in Table 1, utilizing an image-based pre-trained model is effective for video representation learning, leading to superior performance in all downstream tasks. In the last row of the table, we also show the results obtained by utilizing a fully-supervised pre-trained network (DeiT-ViT [54][3]) as the target network which interestingly has lower performance compared to its self-supervised counterpart, DINO, and the one using language supervision, CLIP. Similar observation has been made in [60] as well for masked feature prediction. We argue that the degradation in the performance of a model trained with full supervision is due to the fact that class-level supervision targets a much narrower set of semantic concepts than purely self-supervised models such as DINO or vision-language models such as CLIP.

Effect of image-based target network architecture. According to Table 1, comparing the results obtained by using SwAV [7] with Resnet50-w2 and DINO [8] and CLIP [49] with ViT clearly shows the benefit of using ViT over standard convolutional models even with the same number of parameters. This superiority may come from better feature representation thanks to ViT's self-attention mechanism.

Effect of ensembling image-based models. The results shown in Table 2 indicate the effect of using multiple image-based models instead of one [4]. While using DINO and CLIP together leads to an improvement in downstream tasks compared to a DINO only setting, it not only offers no improvement over CLIP only setting, but also marginally decreases the accuracy on downstream tasks. This may be due to the fact that CLIP's features are expressive enough while not being in complete agreement with DINO's features. Based on this experiment and the results in Table 1, we found CLIP to be the best performing image-based target network and thus we use this model in our comparison with the state-of-the-art. It is clear that with the existence of strong image-based models such as CLIP, adding more constraints by involving more image-based models has negative effect on the performance of downstream tasks.

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[3]Available at https://github.com/facebookresearch/deit
[4]To train such model, Eq. 1 is extended to compute the distance between k with q of each target network.

Table 1: Effect of different image-based models as target network. (*) denotes the fully-supervised model.

method	Image model	k-NN	HMDB	UCF
ρBYOL	-	33.2	57.7	87.3
iBoot	SwAV-R50-w2	38.8	57.4	89.0
iBoot	DINO-ViT	48.0	59.6	89.6
iBoot	CLIP-ViT	53.1	66.5	92.6
iBoot	DeiT-ViT*	45.6	60.6	88.8

Table 2: Effect of ensembling image-based models.

Image model	k-NN	HMDB	UCF
DINO-ViT	48.0	59.6	89.6
CLIP-ViT	53.1	66.5	92.6
DINO+CLIP	52.6	64.3	92.4

Table 3: Effect of additional SSL loss using momentum encoder as target network.

Image model	k-NN	HMDB	UCF
DINO-ViT	48.0	59.6	89.6
DINO+SSL	48.8	60.3	90.6
CLIP-ViT	53.1	66.5	92.6
CLIP+SSL	51.2	64.5	92.2

Table 4: Effect of applying temporal pooling on the features of online and target networks.

Image model	T. Pool	k-NN	HMDB	UCF
DINO-ViT	✗	48.0	59.6	89.6
DINO-ViT	✓	48.4	62.1	91.0
CLIP-ViT	✗	53.1	66.5	92.6
CLIP-ViT	✓	54.3	68.6	94.0

Effect of additional SSL loss. In this experiment, we extend the iBoot pipeline by adding another video encoder branch as an additional target network, parameterized with θ_m which is the exponential moving average of the online parameters θ. To train this pipeline, we optimize the parameters via a cosine distance loss for each online-target network pair. According to the results in Table 3, although adding this SSL loss is slightly effective when using DINO model as the image-based model, it marginally harms the performance when utilizing CLIP as the image-based target network. This experiment clearly shows that using an image-based pre-trained model allows us to skip adding momentum encoder(s), which itself comes at the cost of additional computational overhead. Note that ρBYOL works by enforcing consistency among different views. In our method, the video encodings $f_\theta(v_1)$ and $f_\theta(v_2)$ are encouraged to be consistent by predicting the same latent variable $f_\phi(v_{ref})$.

Effect of applying temporal pooling on the output. The image-based target network produces T features for the input clip. Since we use the Slow pathway of [18] as our online video encoder, our online network also produces T features. One natural choice is to compute the loss on each frame separately. However, we empirically observe the benefit of aggregating feature maps of a clip before computing the loss on multiple downstream tasks. Table 4 demonstrates this when we use temporal average pooling as our aggregation function, with consistent improvement achieved across multiple target networks and downstream tasks.

Effect of number of temporal views. Here, we study the effect of the number of temporal views within a sequence. To this end, we compare three scenarios: (i) $v_1 = v_{ref}$, where we use only one clip as the input to both online and target network, (ii) v_{ref} and v_1, wherein we use v_{ref} as the input to the target network and v_1 as the input to the online network, and (iii) v_{ref}, v_1, and v_2, wherein we use three separate clips per sequence, one acting as the input to the target network and the other two acting as the inputs to the online network (our original setting, as shown in Figure 1 and explained in Sec. 3). Table 5 summarizes the results of these three scenarios. Results on the K400 K-NN classification clearly suggests having three separate views is advantageous compared to the other two cases. However, results on HMDB51 and UCF101 show on-par performance for all three scenarios. This is mainly due to the fact that spatial information is of more importance on these dataset, such clues can be learned with almost any number of views when using a strong image-based target network. To confirm this, we also add the results on SSv2 dataset, where as opposed to other datasets, temporal cues are of significant importance in discriminating between actions. The results on SSv2 suggest that adding more views, i.e., having v_{ref}, v_1, and v_2, help the online video encoder to better learn temporal information. Please note that adding more temporal views may lead to even better performance, as also investigated in [19, 27, 50], however, due to computational budget limitations, this aspect is left for future investigations. Also note, even with v_{ref}, v_1, and v_2, our method outperforms existing methods with more temporal views (see Table 10).

Effect of larger batch size and number of epochs during pre-training. We conduct different configurations in Table 6 in terms of batch size and number of epochs during the pre-training. Unsurprisingly, training for more epochs and larger batch size typically leads to an improvement in the performance of the downstream tasks. However, Table 6 shows that our model also converges

Table 5: Effect of number of temporal views for the online network.

#views	k-NN	HMDB	UCF	SSv2
-	52.7	68.4	94.5	53.6
1	53.4	68.3	93.7	53.9
2	54.3	68.6	94.0	54.6

Table 6: Effect of using larger batch size and more epochs during pre-training.

#Batch	#Epochs	k-NN	HMDB	UCF
8×13	100	54.3	68.6	94.0
32×13	100	55.0	69.1	94.2
32×13	200	56.2	71.6	95.0

Table 7: Effect of using different backbone architectures for the online network.

Backbone	k-NN	HMDB	UCF
3DResNet-50	54.3	68.6	94.0
3DResNet-101	55.3	70.1	94.6

Table 8: Effect of using a larger pre-training dataset.

Data	k-NN	K400 Lin. Eval.	HMDB	UCF
K400	54.3	69.1	68.6	94.0
K600	55.3	71.4	69.4	94.5

to a reasonable model even after 100 epochs (which can be considered as a small-scale experiment in video SSL). For instance, within 100 epochs our approach achieves the accuracy of 94.2% on UCF101, outperforming the state-of-the-art [19] by a large margin (94.2% versus 88.6%) with similar number of training epoch. This clearly shows the effect of using a pre-trained image-based target network in faster convergence more efficiently.

Effect of different backbone architectures for video encoder. Table 7 compares different backbone architectures for the video encoder (online branch). In particular, we compare 3DResNet-50 and 3DResNet-101 backbones. It is clear that using a deeper architecture is more effective in video SSL and improves the downstream tasks performance at the cost of more computational resources.

Effect of using a larger pre-training dataset. The results shown in Table 8 illustrate the effect of pre-training on the larger-scale K600 [9] compared to K400. As expected, this experiment indicates the benefits of using larger-scale datasets for self-supervised pre-training in all downstream tasks.

Effect of video encoder initialization. Typically, video SSL methods start training the video encoders from scratch. While this is a valid solution, we also investigate the effect of starting from a better initialization for the video encoders, the result of which is shown in Table 9. Specifically, the second row shows the results of a model started from the inflated weights of a ResNet-50 network pretrained on ImageNet1K with self-supervision [24]. The improvement achieved by such initialization demonstrates the effectiveness of incorporating

Table 9: Effect of video encoder initialization. Note that all baselines are trained for 200 epochs and batch size of 13×32.

Method	k-NN	HMDB	UCF
ρBYOL (from scratch)	46.6	64.1	91.2
ρBYOL (inflated)	50.1	65.4	92.2
iBoot	56.2	71.6	95.0

learned image representation into the the video SSL model. While such initialization is effective, iBoot outperforms such pre-training by large margin thanks to the freedom in selecting an arbitrary target network architecture.

4.4 Comparison with the state of the art

Table 10 presents a comprehensive comparison to existing video SSL methods that, as ours, use the K400 dataset for pre-training and ResNet-50 as the video encoder backbone. This table reports the results on a number of downstream tasks including linear evaluation on K400, fine-tuning on UCF101, HMDB51 and SSv2. We emphasize that according to various experimental settings different approaches utilize, a strictly direct comparison is not feasible. To better compare to these approaches, we additionally provide the number of pre-training epochs, $T \times \tau$, and number of views (ρ).

Although iBoot is trained efficiently for only 200 epochs with $T = \tau = 8$ and $\rho = 2$, it outperforms existing approaches, including the ones trained for longer on more views with larger input sizes. As clearly shown in our results in Table 10, thanks to its ability to capture strong semantic patterns guided by strong pre-trained image-based Vision Transformer models such as CLIP, iBoot is capable of learning strong video representations, evidenced by superior Top-1 accuracy compared to the existing methods. This is not only shown to be effective in spatially-heavy datasets such as K400 and UCF101, but also in the challenging datasets such as SSv2, where the temporal information is a strong

Table 10: Comparison with state-of-the-art. (*) means averaged over 3 splits.

	Pre-training			Evaluation			
Method	Data	Epoch	$T \times \tau$	K400 lin.eval	UCF101	HMDB51	SSv2 (setting)
Fully Supervised	Scratch	-	8×8	74.7	42.7	18.4	48.8 (1 v, 8×8)
Fully Supervised	K400	-	8×8	N/A	96.6	76.4	52.8 (1 v, 8×8)
CVRL [48]	K400	800	16×2	66.1	92.9	67.9	-
($\rho = 4$) CORP$_m$ [27]	K400	800	16×2	59.1	-	-	61.0 (30 v, 32×1)
CORP$_f$ [27]	K400	800	16×2	66.3	93.5	68.0	-
MoDist [64]	K400	600	8×8	-	94.0	67.4	57.4 (- v, 16×8)
($\rho = 2$)BYOL [19]	K400	200	8×8	65.8	92.7	-	54.4 (1 v, 8×8)
($\rho = 3$)BYOL [19]	K400	200	8×8	68.3	93.8	-	**55.8** (1 v, 8×8)
($\rho = 4$)BYOL [19]	K400	200	8×8	70.0	94.2*	72.1*	-
($\rho = 3$)SimCLR [19]	K400	200	8×8	62.0	87.9	-	52.0 (1 v, 8×8)
($\rho = 3$)SwAV [19]	K400	200	8×8	62.7	89.4	-	51.7 (1 v, 8×8)
($\rho = 3$)MoCo [19]	K400	200	8×8	67.3	92.8	-	54.4 (1 v, 8×8)
iBoot	K400	200	8×8	**71.8**	**95.0** / 94.5*	71.6 / 70.2*	**55.8** (1 v, 8×8) / **61.5** (3 v, 8×8) / **63.0** (3 v, 16×8)

cue to reason about action labels, outperforming its fully-supervised version pre-trained on K400 with a large margin. Apart from the methods presented in Table 10, there exists other approaches that require drastically heavier computations. For instance, BraVe [50] trains four streams of video encoders for 600 epochs, each taking as input clips of either 16 or 64 frames. It also uses clips of 32 frames for all downstream tasks. While iBoot demands much less computation for pre-training and for downstream tasks, it outperforms BraVe [50], e.g., achieving 95.2 (versus 94.7) on UCF101, when using 32 frames for downstream task only.

Finally, the superior performance of iBoot is further confirmed by our experiments on the semi-supervised action recognition on K400, shown in Table 11, targeting highly challenging scenario of accessing to only 1% and 10% of the labeled data, as described in Section 4.2. Note that we report the results for ρBYOL [19] in Table 11 by borrowing its publicly available checkpoint [5] and fine-tuning it with similar setting as iBoot.

Table 11: Semi-supervised classification top-1 on K400.

Method	1% Labels	10% Labels
Supervised	4.5%	34.1%
SimCLR infla. [48]	11.8%	46.1%
ImageNet infla. [48]	16.0%	49.1%
CVRL [48]	35.1%	58.1%
CORP$_f$ [27]	34.8%	58.6%
($\rho = 2$)BYOL [19]	37.2%	60.2%
iBoot	**40.1%**	**61.7%**

5   Discussion

Conclusion. In this work, we propose iBoot, as a video representation learning pipeline, that during training encourages the video encoder to subsume the semantic content of an image-based foundation model trained on a general domain. Since, image-based models have learnt to represent images expressively, we empirically show that we can skip re-doing this for learning spatial aspects of the video. Our results on different downstream tasks have shown the benefits of relying on strong learned image representations in a self-supervised or weakly-supervised manner.

Limitations and Societal impacts. Despite the effectiveness of iBoot as a video representation learning framework, there are some limitations and rooms for improvement. For instance, iBoot relies on a pre-trained image foundation model, trained on an image dataset. This may introduce biases to our video SSL approach when it comes to learning spatial aspect of the videos. While this may be an important issue, further investigation on the bias introduced by the foundation model is out of scope of this work. Additionally, similar to existing video SSL approaches, iBoot is trained on

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[5]Available at `https://github.com/facebookresearch/SlowFast`.

Kinetics dataset comprising only trimmed videos. Evaluating the behavior of iBoot when dealing with uncurated data is yet to be seen, left for future explorations.

On societal impact aspect, we note that iBoot gets benefits from CLIP [49]. CLIP itself is trained on unfiltered and uncurated image-text pairs collected from the internet, resulting in learning many social biases. While a great effort has been made in the original work [49] to provide preliminary analysis of some of these biases in the model, we hope that the future research focuses more on the shortcomings and social biases of such models.

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6 Appendix

In Algorithm 1, we provide the pseudo-code of iBoot training loop. Following our discussion in Section 3 of the main paper, given an image-based foundation model, we utilize different views, v_{ref}, v_1, and v_2, randomly sampled and augmented from a sequence. While v_{ref} acts as the input to the target network, we pass v_1 and v_2 to the online network and we simply encourage the features of v_1 and v_2 produced by the online network to match that of the target one by minimizing the cosine distance loss.

Algorithm 1 iBoot Training Loop

Input:

  f_θ $\triangleright$ online network (video encoder)

  f_ϕ $\triangleright$ target network (image-based pre-trained model)

  W $\triangleright$ linear transformation mapping

for v in loader **do** $\triangleright$ load a minibatch v with n samples, each with T frames

    $v_{ref}, v_1, v_2 = \mathcal{T}(v), \mathcal{T}(v), \mathcal{T}(v)$ $\triangleright$ $\mathcal{T}$ is a random set of spatio-temporal augmentations

    v_{1-2} = Concat($[v_1, v_2]$)

    $k = W(f_\theta(v_{1-2}))$

    v_{ref} = Reshape(v_{ref}) $\triangleright$ $n, T \rightarrow n \times T$

    $q = f_\phi(v_{ref})$ $\triangleright$ output [CLS] token if f_ϕ is ViT model

    q = Reshape(q) $\triangleright$ $n \times T \rightarrow n, T$

    q = Concat($[q, q]$)

    loss = $2 - 2 . \frac{\langle q , k \rangle}{\|q\|_2 . \|k\|_2}$

    loss.backward()

    update(f_θ)

end for