Learning Representational Invariances for Data-Efficient Action Recognition

Yuliang Zou\textsuperscript{a}, Jinwoo Choi\textsuperscript{b,**}, Qitong Wang\textsuperscript{c}, Jia-Bin Huang\textsuperscript{d}

\textsuperscript{a}Department of Electrical and Computer Engineering, Virginia Tech, VA, USA
\textsuperscript{b}Department of Computer Science and Engineering, Kyung Hee University, Yongin, Korea
\textsuperscript{c}Department of Computer and Information Sciences, University of Delaware, DE, USA
\textsuperscript{d}Department of Computer Science, University of Maryland College Park, MD, USA

ABSTRACT

Data augmentation is a ubiquitous technique for improving image classification when labeled data is scarce. Constraining the model predictions to be invariant to diverse data augmentations effectively injects the desired representational invariances to the model (e.g., invariance to photometric variations) and helps improve accuracy. Compared to image data, the appearance variations in videos are far more complex due to the additional temporal dimension. Yet, data augmentation methods for videos remain under-explored. This paper investigates various data augmentation strategies that capture different video invariances, including photometric, geometric, temporal, and actor/scene augmentations. When integrated with existing semi-supervised learning frameworks, we show that our data augmentation strategy leads to promising performance on the Kinetics-100/400, Mini-Something-v2, UCF-101, and HMDB-51 datasets in the low-label regime. We also validate our data augmentation strategy in the fully supervised setting and demonstrate improved performance.

© 2022 Elsevier Ltd. All rights reserved.

1. Introduction

Deep neural networks have shown rapid progress in video action recognition (Simonyan and Zisserman, 2014; Carreira and Zisserman, 2017; Tran et al., 2017; Xie et al., 2018; Feichtenhofer et al., 2019; Lin et al., 2019; Feichtenhofer, 2020; Yang et al., 2020). However, these approaches rely on training a model on a massive amount of labeled videos. For example, the SlowFast networks (Feichtenhofer et al., 2019), R(2+1)D (Tran et al., 2017), and I3D (Carreira and Zisserman, 2017) are pre-trained on the Kinetics-400 dataset (Kay et al., 2017), containing 300K ∼ 650K manually labeled and temporally trimmed videos. The dependency on large-scale annotated video datasets is not scalable because manual labeling of videos is expensive, time-consuming, and error-prone. Hence, it is of great interest to investigate new approaches to improve data efficiency.

Data augmentation is a simple yet effective approach for improving data efficiency. Early work uses simple/weak augmentations to generate additional realistic-looking samples by applying geometric transformations (e.g., random scaling and cropping). Such approaches have been widely used in training supervised image classification models (Krizhevsky et al., 2012; He et al., 2016; Huang et al., 2017). While many realistic-looking visual examples are generated, these weak augmentations are ineffective in increasing the training data diversity because the augmented samples remain highly similar to the original ones. Recently, diverse/strong augmentations have been proposed (Cubuk et al., 2019, 2020; Lim et al., 2019). By applying aggressive photometric and geometric transformations to the original data, strong augmentations help generate diverse training data and improve model performance in the supervised learning setting. Later, strong data augmentations have also shown their potential in consistency-based semi-supervised learning frameworks (Sohn et al., 2020; Xie et al., 2020). The intuition behind the success of strong data augmentations in supervised and semi-supervised settings lies in learning representational invariances via regularizing a model to generate consistent predictions for diverse augmented views of the same data.

In this paper, we investigate and study strong data augmentation for video. While strong data augmentation in the image domain has been extensively studied (DeVries and Taylor, 2017; Cubuk et al., 2019; Lim et al., 2019; Yun et al., 2019; Cubuk et al., 2020), data augmentation techniques for videos remain...
under-explored. Recent self-supervised video representation learning approaches (Han et al., 2019; Tschannen et al., 2019; Xu et al., 2019; Wang et al., 2020a; Qian et al., 2021) show the benefits of leveraging some specific video invariances (i.e., spatial, temporal, etc.). However, these approaches only utilize partial aspects of the desired representation invariances. In contrast, we provide a comprehensive study in semi-supervised and fully-supervised settings. As shown in Figure 1, we explore the following invariances: photometric (color), geometric (spatial), temporal, scene (background), and investigate the corresponding data augmentation strategies that encourage the model learning these invariances.

Our results show that all these augmentation techniques help improve performance. With all the augmentations (as shown in Figure 2), we achieve favorable results on the Kinetics-100 (Jing et al., 2021), UCF-101 (Soomro et al., 2012), and HMDB-51 (Kuehne et al., 2011) datasets in both low-label and full-label settings.

To summarize, we make the following contributions.

- We study various strong video data augmentation strategies for data-efficient action recognition.
- We introduce a novel scene augmentation strategy, ActorCutMix, to encourage scene invariance, which is crucial for action recognition.
- Our strong data augmentation strategies significantly improve the data efficiency in both the semi-supervised and fully-supervised learning settings, achieving promising results in standard video action recognition benchmarks.
- Our source code and pre-trained models are publicly available at https://github.com/vt-vl-lab/video-data-aug.

2. Related Work

Video recognition models. Recent advances in video recognition focus on improving the network architecture design (e.g., two-stream networks (Simonyan and Zisserman, 2014; Feichtenhofer et al., 2016), 3D CNNs (Tran et al., 2015; Carreira and Zisserman, 2017; Hara et al., 2018; Wang et al., 2018), 2D and 1D separable CNNs (Tran et al., 2017; Xie et al., 2018), video Transformers (Arnab et al., 2021; Fan et al., 2021; Liu et al., 2022), incorporating long-term temporal contexts (Wang et al., 2018; Feichtenhofer et al., 2019; Wu et al., 2019)), and training efficiency (Wu et al., 2020). Our focus in this work lies in improving data efficiency of video action classification by exploring data augmentation strategies from various perspectives: photometric, geometric, temporal, and actor/scene.

Data augmentation. Data augmentation is an essential component in modern deep neural network training. Early approaches (Laine and Aila, 2016; Sajjadi et al., 2016) only apply weak augmentations such as random translation and cropping. Depending on the downstream tasks, various invariances are needed to improve the performance. For instance, random Gaussian, Dropout noise (Bachman et al., 2014) and adversarial noise (Miyato et al., 2018) have also been proposed for semi-supervised learning, leading to improved performance. Sometimes, data augmentation techniques are used to encourage models sensitive to variances to certain transformations: rotation (Gidaris et al., 2018) and time-shift (Patrick et al., 2021) in video. Learning-based data augmentation approaches (Cubuk et al., 2019; Lim et al., 2019) aim to avoid the manual design of data transformations. Such networks learn to adjust the data augmentation policy according to the feedback on a held-out (labeled) validation set. In semi-supervised classification, recent methods (Sohn et al., 2020; Xie et al., 2020) apply strong image space augmentations (e.g., RandAugment (Cubuk et al., 2020)) by cascading color jittering, geometric transformations, and regional dropout (DeVries and Taylor, 2017; Yun et al., 2019), achieving state-of-the-art performance. Instead of perturbing the unlabeled images in the pixel space, several approaches (Kuo et al., 2020; Wang et al., 2020b) propose to augment training examples in the feature space to complement conventional image space augmentations, providing further improvement.

Most existing works design the data augmentation strategy specifically for images. There are only a few works on data augmentation for video action recognition (Yun et al., 2020; Zhang et al., 2020; Patrick et al., 2021). Similar to our ActorCutMix augmentation. VideoMix (Yun et al., 2020) cuts and pastes a spatio-temporal cube from one video to another video. However, VideoMix does not consider human regions during the cut and paste operation, while the proposed ActorCutMix explicitly cuts
and pastes human regions from one video to another. In this work, in the context of data-efficient video action recognition, we extensively study data augmentation from various perspectives: photometric, geometric, temporal, and actor/scene.

**Semi-supervised learning.** Semi-supervised learning (SSL) improves the performance using abundant unlabeled data, alleviating the need for manual annotations. Most recent SSL approaches adopt either one of the following two strategies: (1) consistency regularization (Laine and Aila, 2016; Sajjadi et al., 2016; Tarvainen and Valpola, 2017; Miyato et al., 2018; Kuo et al., 2020; Xie et al., 2020), and (2) entropy minimization (Grandvalet and Bengio, 2005; Lee, 2013). The key insight of consistency regularization is that a model should generate consistent predictions for the same (unlabeled) data undergone different transformations/perturbations. Recently, holistic approaches (Berthelot et al., 2019, 2020; Sohn et al., 2020; Xie et al., 2020) that combine both the SSL strategies (consistency and entropy minimization) have been proposed to tackle the semi-supervised image classification task effectively. The consistency regularization within these SSL frameworks effectively encourages representational invariances to strongly-augmented views.

In the low-label settings, we leverage the FixMatch framework (Sohn et al., 2020) to validate the efficacy of our video data augmentations. We also demonstrate improved results when integrating our augmentation strategies with another recent SSL framework, UDA (Xie et al., 2020).

A few recent works propose to apply the SSL framework to the video domain (Jing et al., 2021; Singh et al., 2021). They focus on algorithmic improvement for video SSL. In contrast, our work complements these recent advances by exploring strong data augmentation strategies for videos.

**Self-supervised learning.** Self-supervised learning is a technique used to learn representations when external labels are unavailable, e.g., unsupervised setting. In the self-supervised learning framework, people define pretext tasks that are expected to be useful for learning more generalizable representations. In video domain, there have been pretext tasks for frame sorting (Lee et al., 2017), clip order verification (Misra et al., 2016) and prediction (Xu et al., 2019), speed prediction (Epstein et al., 2020; Benaim et al., 2020), and future prediction (Han et al., 2019, 2020).

Recently, contrastive learning has emerged as a powerful tool for learning visual representations (Sermanet et al., 2018; Han et al., 2019; Chen et al., 2020a,b; He et al., 2020; Purushwalkam and Gupta, 2020; Singh et al., 2021; Xiao et al., 2021). In contrastive learning, a model learns representations by instance discrimination. These methods encourage feature embeddings from different augmentations of the same data to be similar and feature embeddings from different data instances to be dissimilar to each other. Contrastive learning can be viewed as injecting visual invariances. It pulls the representations of different augmented views of the same instance together, enforcing invariances to the selected data augmentations. To further demonstrate the effectiveness of our augmentation strategy, we validate its compatibility with contrastive learning. Instead of injecting visual invariances in pure self-supervised learning, we conduct experiments in a semi-supervised learning setting by replacing the consistency regularization with a contrastive objective, following Singh et al. (2021).

### 3. Video Data Augmentations

We explore strong and diverse video data augmentations mainly in the low-label setting. We formulate low-label video action recognition as a semi-supervised classification problem.

We first describe a consistency-based semi-supervised classification formulation in Section 3.1. Then we present our *intra-clip* data augmentation strategies (photometric, geometric, temporal) in Section 3.2. Next, we propose a *cross-clip* human-centric data augmentation operation, ActorCutMix, in Section 3.3. We describe how we combine all these data augmentation operations to construct the final strong data augmentation strategy in Section 3.4.

#### 3.1. Consistency-based semi-supervised learning

Considering a multi-class classification problem, we denote $X = \{ (x_i, y_i) \}_{i=1}^{N_l}$ as the labeled training set, where $x_i \in \mathbb{R}^{T \times H \times W \times 3}$ is the $i$-th sampled video clip, $y_i$ is the corresponding one-hot ground truth label, and $N_l$ is the number of data points in the labeled set. Similarly, we denote $U = \{ x_i \}_{i=1}^{N_u}$ as the unlabeled set, where $N_u$ is the number of data points in the unlabeled set. We use $f_\theta$ to denote a classification model with trainable parameters $\theta$. We use $\alpha(\cdot)$ to represent the weak (standard) augmentation (i.e., random horizontal flip, random scaling, and random crop in video action recognition), and $\beta(\cdot)$ to represent the strong data augmentation strategies (our focus).

We present an overview of the state-of-the-art semi-supervised classification pipeline (Sohn et al., 2020) in Figure 2. We denote an input video clip consists of $T$ frames as $x_i$ throughout the paper. Given a mini-batch of labeled data $\{(x_i, y_i)\}_{i=1}^{B_l}$, we
minimize the standard cross-entropy loss $L_t$ defined as

$$L_t = -\frac{1}{B_t} \sum_{i=1}^{B_t} y_i \log f_0(\alpha(x_i)).$$  \hfill (1)

For a mini-batch of unlabeled data $\{x_j\}_{j=1}^{B_u}$, we enforce the model prediction consistency. More specifically, we generate pseudo-label $\hat{y}_j$ for the unlabeled data via confidence thresholding

$$C = \{x_j | \text{max} f_0(\alpha(x_j)) \geq \tau\},$$  \hfill (2)

where $\tau$ denotes a pre-defined threshold and $C$ is the confident example set for the current mini-batch. We then convert the confident model predictions $f_0(\alpha(x_j))$ to one-hot labels $\hat{y}_j$ by taking argmax operation. We optimize a cross-entropy loss $L_u$ for the confident set of unlabeled examples.

$$L_u = -\frac{1}{B_u} \sum_{j \in C} \hat{y}_j \log f_0(\beta(x_j)).$$  \hfill (3)

Our overall training objective is the summation of (1) and (3).

$$L = L_t + \lambda_u L_u.$$  \hfill (4)

We set $\lambda_u = 1$ and find it performs well empirically.

Note that it is easy to switch from a consistency-based semi-supervised learning framework to a contrastive-learning-based semi-supervised learning formulation, by replacing the consistency regularization in (3) to a contrastive objective. In this paper, we use the temporal contrastive objective proposed in TCL (Singh et al., 2021) to further demonstrate the effectiveness of our video data augmentations. We refer to Singh et al. (2021) for more details.

### 3.2. Intra-clip data augmentation

**Temporally-coherent photometric and geometric augmentation.** Moderate photometric (color) and geometric (spatial) variations often do not affect the class semantics (e.g., object classification). Thus, photometric and geometric augmentation strategies are widely used in supervised (Cubuk et al., 2020), self-supervised (Chen et al., 2020a; He et al., 2020), and semi-supervised (Sohn et al., 2020) image classification tasks. Similar to image classification, videos from the same class also exhibit photometric (color) and geometric (spatial) variations (Figure 1(a-b)). It is thus natural to apply photometric and geometric data augmentation for video classification. However, as we validate with an ablation study in Section 4.1.2, individually applying state-of-the-art photometric and geometric augmentations (e.g., RandAugment (Cubuk et al., 2020)) on each video frame leads to sub-optimal performance. We conjecture that the random transformations for each frame break the temporal coherency of a video clip. As a result, the frame-wise inconsistency within video clips may cause adverse effects on the learned representations. A recent work (Qian et al., 2021) also validates the above assumption in the context of self-supervision video representation learning. Thus, we apply the same photometric and geometric transformations for every frame to maintain the temporal consistency within a sampled video clip. Specifically, we sample two basic operations from a pool of photometric and geometric transformations (as in RandAugment (Cubuk et al., 2020)) and then apply them to every frame for each video clip.

**Temporal augmentation.** In addition to color space and spatial dimension, videos have a temporal dimension. The additional temporal dimension significantly increases the variability of video data from many perspectives (e.g., speed, sampling rate, temporal order, etc.). To capture these task-specific representational invariances, we introduce and study three different types of temporal transformations: (1) T-Half, (2) T-Drop, and (3) T-Reverse. We illustrate the three temporal augmentations in Figure 3. First, to avoid a video recognition model focusing too much on particular frames instead of understanding the temporal context, we randomly drop some frames within a video clip. Randomly dropping frames is conceptually similar to the artificial occlusion augmentations, e.g., Cutout (DeVries and Taylor, 2017) operations in the spatial dimension in the image domain. We implement a temporal extension of Cutout in two ways: 1) We randomly discard the second half of a video clip and fill in the empty slots with the first half, T-Half. 2) For each frame in a video clip, we randomly replace it with its previous frame with a probability of $p = 0.5$, which we refer to as T-Drop. In addition to dropping part of the information, T-Drop also simulates *speeding-up* (frame indexes: $[2, 3] \rightarrow [1, 3]$) and *slowing-down* (frame indexes: $[1, 2] \rightarrow [1, 1]$) as shown in Figure 3) within a video clip. Such temporal augmentation regularizes the video classification model to generate consistent predictions for the two video clips (original and augmented ones) with different speed and temporal occlusion, implicitly encoding the speed/occlusion invariance. Second, we observe that many actions have cyclic temporal structures and thus can be recognized no matter in the original chronological order or reverse. To capture this invariance of temporal order, we transform a video clip by reversing its temporal order, referred to as T-Reverse. As validated in the ablation study (Section 4.1.2), all three operations are beneficial for SSL video action recognition. Since these operations are complementary to each other, we put them in an operation pool (including the *identity* operation) and randomly sample one for each input video clip.

**Discussions.** We encourage three types of temporal invariances during model training by applying the aforementioned temporal augmentation. (1) Invariance to partial temporal occlusion (T-Half and T-Drop): This invariance enforces models to recognize
actions even with partial evidence. For example, humans can recognize the “Basketball” action by seeing only the first half (seeing bent arms with a ball, stretching arms but not seeing a ball flying). (2) Invariance to speed (T-Drop): The same action can be performed at a different speed. A model could also encounter videos containing the same actions but different frame rates. Hence, encouraging action recognition models to be invariant to different speeds will be helpful. (3) Invariance to temporal (reverse) order (T-Reverse): For example, cyclic/order invariant actions such as “push/pull-ups”, “punching bags”, and many instrument-playing actions are invariant to reversed order. More than 50% of classes in standard human action recognition benchmarks are cyclic/order-invariant (e.g., 57 out of 101 in UCF-101 and 28 out of 51 in HMDB-51).

We validate the effectiveness of these temporal invariances in Table 2(b). Here, we discuss the limitation as well. First, for fine-grained action recognition (Goyal et al., 2017; Madhisoni et al., 2018), a model may need to utilize the information from all the input frames to make a prediction. Also, speed difference may play a key role in discriminating the subtle differences between two similar actions (e.g., jogging v.s. running). Partial temporal occlusion invariance and speed invariance could hurt the overall performance in this case. Second, suppose we want to discriminate action classes with symmetric temporal orders (e.g., move an object from left to right v.s. move an object from right to left). In that case, encouraging temporal order invariance can be harmful. However, we find all three temporal invariances helpful for general coarse-grained human action recognition purposes, particularly in a low-label regime. Note that the users can always decide which temporal invariance to inject on specific video tasks.

3.3. Cross-clip data augmentation

ActorCutMix. There are severe scene representation biases (Li et al., 2018; Choi et al., 2019; Li and Vasconcelos, 2019) in the popular action recognition datasets such as UCF-101, HMDB-51, Kinetics-400, Charades (Sigurdsson et al., 2016), and ActivityNet (Fabian Caba Heilbron and Niebles, 2015), etc. Action recognition models trained on these scene-biased datasets tend to leverage the background scene information instead of actual action (Choi et al., 2019). These scene-biased action recognition models are likely to fail when tested on the new data with unseen actor-scene combinations. For example, people can do “Fencing” either in a gym or in a forest, as shown in the scene invariance block in Figure 1(d). Training a model on the data consisting of “Fencing” actions in gyms only will likely fail when tested on the new data consisting of “Fencing” actions in forests. To mitigate the scene bias, we propose a new human-centric video data augmentation method, ActorCutMix. The operation of the proposed ActorCutMix is similar to CutMix (Yun et al., 2019) in mixing the pixels from different samples to create new training data. However, our method differs in motivation. ActorCutMix aims to improve scene invariance, regularizing a video classification model to focus on the actor to make predictions (i.e., scene debiasing). In contrast, the goal of CutMix is to achieve occlusion robustness, encouraging a model to make correct predictions even when part of the image input is occluded.

As shown in Figure 4, ActorCutMix generates new training examples (x_\hat{A}, y_\hat{A}), (x_B, y_B) by swapping the background regions in the two training examples (x_A, y_A), and (x_B, y_B) in a mini-batch, where x is a video clip and \hat{y} is the corresponding pseudo-label. We define the swapping operation as follows:

\[ \tilde{x}_A = m_A \odot x_A + (1 - m_A) \odot (1 - m_B) \odot x_B, \]
\[ \tilde{y}_A = \hat{y}_A. \]  

Here, \( m \in \mathbb{R}^{T \times H \times W \times 3} \) is a binary human mask for a video clip, with a value of 1 for human regions and 0 for the background regions. \( \odot \) represents the element-wise multiplication. The other augmented training sample and its pseudo label (\( \tilde{x}_B, \tilde{y}_A \)) can be generated similarly. We generate the human mask \( m \) by running an off-the-shelf human detection algorithm (He et al., 2017; Yang et al., 2019). We run the human detector on the video datasets offline and load the cached human bounding boxes during training. We demonstrate that ActorCutMix significantly improves the semi-supervised action recognition performance in Section 4.1.2.

Discussions. ActorCutMix injects the scene invariance into the model, mitigating the reliance on the scene context. In other words, we encourage a model to recognize the action class by focusing on the actor, regardless of the background scene. Without proper regularization, deep neural networks tend to learn shortcuts (DeVries and Taylor, 2017; Singh and Lee, 2017; Geirhos et al., 2018; Hendricks et al., 2018; Yun et al., 2019). Action recognition models could learn spurious correlations between the action and the scene instead of focusing on the human action itself (Choi et al., 2019; Bahng et al., 2020), i.e., predicting the action class according to the scene context only. In this work, we regularize the network to focus on human actions by providing diverse background context for each action.

Label smoothing. In Eqn. (5), we assign the pseudo label of the human action \( \hat{y}_A \) to the video clip A by assuming a perfect human detector. In other words, we aim to recognize the human action instead of the background scene. However, human detectors are imperfect in general. Due to missing/false-positive human detections, augmented video clips could potentially contain humans performing different actions from different clips. Therefore, to prevent model confusion, we apply label smoothing with a
higher weight for the label of the (potentially corrupted) human action \( \hat{y}_A \) and a lower weight for the label of the (potentially corrupted) background scene \( \hat{y}_B \) as follows.

\[
\hat{y}_A = \lambda \hat{y}_A + (1 - \lambda) \hat{y}_B. \tag{6}
\]

\[
\lambda = 1 - \left| 1 - \frac{\sum m_A}{THW} \right|. \tag{7}
\]

Here, \( \sum m_A/THW \in [0, 1] \) is the foreground (human) ratio, and \( \alpha \) is a hyperparameter that controls the influence of the pseudo label of the human region. We empirically find \( \alpha = 4 \) yields good results.

We emphasize that ActorCutMix and CutMix have different purposes of label smoothing. Label smoothing in CutMix aims to provide multiple labels for a single training image. For example, a training image consists of information from two different classes (e.g., a dog and a cat). In contrast, we smooth labels in ActorCutMix to mitigate data corruption due to the missing/false-positive human detections. The proposed label smoothing can further boost performance as shown in Table 2(c).

**Limitations.** Scene invariance also has its limitation. For example, if our goal is to discriminate different actions in the same background context (e.g., the Diving48 dataset (Li et al., 2018)), ActorCutMix makes no difference. Also, the current combination of the actors and the scenes could cause visual artifacts that may be harmful, as shown in other copy and paste-based augmentations (DeVries and Taylor, 2017; Yun et al., 2019; Kim et al., 2020; Yoo et al., 2020). More accurate segmentation of the actors and objects may further improve the performance. We leave it as a future direction.

### 3.4. Combining different data augmentations

We provide the algorithm outline of our strong data augmentation strategy for video in Algorithm 1.

**Combining photometric-geometric and temporal augmentations.** We combine the photometric-geometric and temporal augmentations by cascading both of them. The cascaded combination can be regarded as a spatial-temporal counterpart of RandAugment (Cubuk et al., 2020): Randomly sample two operations from photometric and geometric augmentation operations, and then sample one operation from the temporal augmentation operations. We refer this combined augmentation as *intra-clip augmentation*.

**Combining intra-clip and cross-clip augmentations.** To combine intra-clip augmentation (photometric-geometric-temporal) and cross-clip augmentation (ActorCutMix), we propose randomly applying either one of them for each mini-batch. We validate the effectiveness of this combination in Section 4.1.2.

### 4. Experimental Results

To validate our strong data augmentation strategy, we conduct three types of experiments: i) consistency-based semi-supervised learning in Section 4.1, ii) contrastive learning-based semi-supervised learning in Section 4.2, iii) fully-supervised learning in Section 4.3.

**Algorithm 1: Strong video data augmentation**

**Input:** A mini-batch of unlabeled video clips \( X \) and the corresponding human mask \( M \)

1. Draw a sample \( p \) from uniform distribution \( U(0, 1) \)
2. If \( p > 0.5 \)
3. Reverse the order of the batch dimension to get \( X' \) and \( M' \)
4. \( \tilde{X}, \tilde{X}' = \text{ActorCutMix}(X, X', M, M') \)
5. else
6. for each video clip \( x \) in \( X \)
7. Sample \( op_1, op_2 \) from photometric-geometric op pool, \( op_3 \) from temporal op pool
8. \( \tilde{x} = \text{PhotometricGeometricAug}(x, op_1, op_2) \)
9. \( \tilde{x} = \text{TemporalAug}(\tilde{x}, op_3) \)
10. end for
11. end if

**Return:** Strongly-augmented video clips \( \tilde{X} \)

### 4.1. Experimental results on consistency-based SSL

We validate our strong data augmentation strategy by plugging it into consistency-based semi-supervised learning frameworks (i.e., FixMatch (Sohn et al., 2020) and UDA (Xie et al., 2020)). We start with describing experimental setting in Section 4.1.1, then we show ablation experiments in Section 4.1.2. Comparison with state of the arts (Section 4.1.3) and error analysis (Section 4.1.4) are followed.

### 4.1.1. Experimental setup

**Dataset.** We conduct experiments on the public action recognition benchmarks: UCF-101 (Soomro et al., 2012), HMDB-51 (Kuehne et al., 2011), and Kinetics-100 (Jing et al., 2021; Kay et al., 2017). UCF-101 consists of 13,320 videos with 101 action classes. HMDB-51 consists of 6,766 videos with 51 action classes. The full Kinetics dataset consists of 300K videos with 400 classes. We use a subset, Kinetics-100, consisting of 90K videos with 100 classes. We split the datasets following Jing et al. (2021) to conduct semi-supervised training based on the state-of-the-art FixMatch framework (Sohn et al., 2020).

**Evaluation metrics.** For all the datasets, we report top-1 accuracy for quantitative comparison.

**Compared methods.** As a first baseline, we train a model with only the labeled data using standard/weak video data augmentations (e.g., random scaling, horizontal flipping, etc.). We call it as supervised baseline. In the low-label setting, we also compare

| Symbol | Description | Value |
|--------|-------------|-------|
| \( \tau \) | Pseudo label threshold (Eq. (2)) | 0.95 |
| \( \lambda_u \) | Unlabeled loss weight (Eq. (4)) | 1.0 |
| \( \alpha \) | Scaling factor for label smoothing (Eq. (7)) | 4.0 |
we train our method for 600 epochs with respect to unlabeled data. For the HMDB-51 dataset (Kuehne et al., 2011), we train our method for 360 epochs with respect to unlabeled data. For the UCF-101 dataset (Soomro et al., 2012) using a R(2+1)D ResNet-34 model in the semi-supervised learning setting based on FixMatch (Sohn et al., 2020).

Implementation details. We implement our method on top of the publicly available mmaction2 codebase (Contributors, 2020). Unless specified, we use the R(2+1)D model (Tran et al., 2017) as the feature extraction backbone. To better understand the effect of our augmentation techniques, we initialize the model with random weights (as opposed to using models with supervised pre-training on ImageNet and/or Kinetics). We sample eight frames from each video randomly and uniformly to construct a clip with an eight-frame sampling interval. We use a batch size of 16 clips for the supervised baseline for each GPU. We use a mini-batch of five clips from labeled data and five clips from unlabeled data for each GPU for our semi-supervised learning method. We train our models using 8 RTX 2080 Ti GPUs.

We use SGD with momentum as our optimizer, with an initial learning rate of 0.1, a momentum value of 0.9, and a weight decay value of 5e − 4. We use the cosine annealing policy for learning rate decay. We also adopt synchronous batch normalization across eight GPUs. For the UCF-101 dataset (Soomro et al., 2012) and Kinetics-100 dataset (Kay et al., 2017; Jing et al., 2021), we train our method for 360 epochs with respect to unlabeled data. For the HMDB-51 dataset (Kuehne et al., 2011), we train our method for 600 epochs with respect to unlabeled data. We list the values of the other hyper-parameters as in Table 1.

4.1.2. Ablation study

In the following, we validate each design choice of our strong data augmentation strategy. We conduct ablation experiments on the 20% label split of the UCF-101 dataset (Soomro et al., 2012) using a R(2+1)D ResNet-34 model in the semi-supervised learning setting based on FixMatch (Sohn et al., 2020).

Temporal augmentation. Next, we study the effectiveness of temporal augmentation and its atomic operations. As shown in Table 2(b), all of the atomic operations, i.e., T-Half, T-Drop, T-Reverse, are beneficial to the recognition accuracy. The results validate our motivation: Temporal occlusion, speed, and order invariances are beneficial for coarse-grained human action recognition, improving the data efficiency. With all the atomic temporal operations combined, the final temporal augmentation further improves the accuracy. In addition, we compare our temporal augmentation (TemporalAll) with an existing speed-up and down augmentation baseline (Singh et al., 2021). Our temporal augmentation shows favorable performance compared to the speed-up and speed-down augmentation (44.07% vs. 41.66%).

ActorCutMix augmentation. In Table 2(e), ActorCutMix without label smoothing shows moderate improvement over the supervised baseline. With label smoothing, ActorCutMix shows even more significant performance improvement. The results imply that label smoothing can mitigate data corruption caused by the missing/false-positive human detections. When compared with CutMix (Yun et al., 2019) (43.27%) and Background CutMix (41.85%) where we replace the background instead of replacing humans, ActorCutMix (45.26%) shows significant accuracy improvement. The results validate that capturing scene invariance improves action recognition accuracy. To study the effect of supervision for human detection, we replace the supervised detector (He et al., 2017) with an unsupervised detector (Yang et al., 2019) trained on the UCF-101 dataset. ActorCutMix with an unsupervised detector slightly underperforms
(45.29% → 45.12%) than the ActorCutMix with a supervised detector (both are with label smoothing). We use the supervised human detector for the rest of the experiments.

**Combining photometric-geometric and temporal augmentations.** In this experiment, we study how to combine photometric-geometric augmentation and temporal augmentation. We compare the cascaded strategy with an alternative combination strategy: sample only one of them and apply it for a video clip. As shown in Table 2(d), the cascaded strategy leads to better performance.

**Combining intra-clip and cross-clip augmentations.** We study how to combine both intra-clip (photometric-geometric-temporal) and cross-clip (ActorCutMix) data augmentations. A straightforward approach is cascading these two types of augmentations. As shown in Table 2(e), we find that the cascading intra- and cross-clip augmentations is even worse than applying the intra-clip augmentation without ActorCutMix (50.89% vs. 54.48%). Our intuition is that cascading intra-clip and cross-clip augmentation produces severely distorted clips that no longer resemble natural videos. Randomly applying only one data augmentation selected from intra-clip or cross-clip for each input video clip gives the best top-1 accuracy (56.73%). Hence, we use random sampling for the rest of the paper.

**Improvement over vanilla semi-supervised frameworks.** Lastly, we show that our strong data augmentation is method-agnostic. We plug our strong augmentation into the unlabeled branches of two state-of-the-art consistency-based semi-supervised learning frameworks, FixMatch (Sohn et al., 2020) and UDA (Xie et al., 2020). In Table 2(f), the two semi-supervised learning frameworks with per-frame augmentation are denoted as vanilla. The vanilla+temp.-co. denotes we use temporally coherent photometric/geometric augmentations for strong augmentation. Our strong augmentation consistently improves the performance by a large margin. We show improvement over another semi-supervised action recognition framework, TCL (Singh et al., 2021) in Section 4.2.

**Strong augmentation on the labeled branch.** Currently, the strong data augmentation is only applied to the unlabeled branch by default, as shown in Figure 2. Here, we also conduct an experiment applying the strong augmentation on the labeled branch. It achieves a similar performance (56.46%) as our default setting (56.73%). We conjecture that the strong augmentations have already injected the visual invariances in the unlabeled branch. Additional strong augmentation for the labeled branch may not add extra visual invariances to the model. Therefore, the performance difference is negligible. For better training efficiency, we choose to use the default setting.

**Different initialization.** We investigate whether our strong data augmentation strategy can still improve over the supervised baseline, given strong pre-trained model weights as an initialization. As shown in Table 3, while the improvement over the supervised baseline is not as significant as the boost in the train-from-scratch setting, the proposed method can still achieve a sizable improvement (72.40% → 77.37%). The results validate the general applicability of the strong data augmentation in practical scenarios.

### Table 3. Effect of using different initialization.

| Method          | Random | Kinetics-400 |
|-----------------|--------|--------------|
| Supervised      | 38.91  | 72.40        |
| Ours            | 56.73  | 77.37        |

#### 4.1.3. Comparing with the state of the arts

Next, we compare our method on several established benchmarks, following the same data splits as in Jing et al. (2021). As shown in Table 4, our method consistently achieves favorable performance compared with other approaches with the same amount of supervision. On the UCF-101 dataset, VideoSSL (Jing et al., 2021) achieves better performance in the extremely low label ratios (10% and 5%) than ours while being worse in other label ratios. We hypothesize that the ImageNet pre-trained model’s knowledge distillation plays a crucial role in the extremely low-label regime. The improvement from the distillation might quickly become marginal as the label ratio increases.

**ImageNet Knowledge Distillation.** Following VideoSSL (Jing et al., 2021), we adopt an ImageNet pre-trained ResNet-18 to compute a 1,000 dimensional ImageNet class probability vector for each frame of all the training videos offline. Accordingly, we add a classification head to predict the ImageNet probability of each video clip on top of the feature extraction backbone. We randomly select one frame from each (weakly-augmented) video clip during training time and then use its corresponding ImageNet probability as a soft pseudo label for a cross-entropy loss. The soft pseudo label provides an additional supervisory signal to the feature backbone. As shown in Table 4, our method’s performance significantly improves with ImageNet distillation compared to our method without ImageNet distillation (26.1% → 49.5% in 5% label split and 39.9% → 52.7% in 10% label split of the UCF-101 dataset). Our method with ImageNet distillation shows a favorable performance when compared to VideoSSL (Jing et al., 2021).

**Comparison with self-supervised learning approaches.** With the same amount of data, one can pre-train the model using all the available data (self-supervised learning) and then fine-tune the model with a small amount of labeled data instead of conducting semi-supervised learning. Thus, we establish another type of baselines by fine-tuning the self-supervised video pre-trained models on the labeled data. We choose three recent state-of-the-art self-supervised methods for video representation, i.e., VCOP (Xu et al., 2019), DPC (Han et al., 2019), and MemDPC (Han et al., 2020). As shown in Table 5, our method achieves promising results when compared with these self-supervised approaches across three datasets. Note that these self-supervised learning approaches are complementary to existing semi-supervised learning frameworks. For example, one can first pre-train the feature backbone with a self-supervised learning objective and then fine-tune the network in a semi-supervised manner.
Table 4. Comparison with the state of the arts. All the methods use a 3D ResNet-18 model. The best performance is in bold and the second best is underlined.

| Method                      | w/ ImageNet | Kinetics-100 | UCF-101 | HMDB-51 |
|-----------------------------|-------------|--------------|---------|---------|
|                            | distillation | 20% | 50% | 20% | 10% | 5% | 60% | 50% | 40% |
| PseudoLabel (Lee, 2013)     | -           | 48.0 | 47.5 | 37.0 | 24.7 | 17.6 | 33.5 | 32.4 | 27.3 |
| MeanTeacher (Tarvainen and Valpola, 2017) | -          | 47.1 | 45.8 | 36.3 | 25.6 | 17.5 | 32.2 | 30.4 | 27.2 |
| S4L (Zhai et al., 2019)     | -           | 51.1 | 47.9 | 37.7 | 29.1 | 22.7 | 35.6 | 31.0 | 29.8 |
| VideoSSL (Jing et al., 2021) | ✓     | 57.7 | 54.3 | 48.7 | 42.0 | 32.4 | 37.0 | 36.2 | 32.7 |
| Ours                        | -           | 61.2 | 59.9 | 51.7 | 40.2 | 27.0 | 38.9 | 38.2 | 32.9 |
| Ours                        | ✓           | 68.7 | 64.7 | 57.4 | 53.0 | 45.1 | 40.8 | 39.5 | 35.7 |

4.1.4. Improvement over Supervised Baseline and Error Analysis

In this section, we plug our strong data augmentation into FixMatch (Sohn et al., 2020) and compare it with the supervised baseline, where only labeled video data is used during training (labeled branch only in Figure 2). Note that we train both our model and the supervised baseline from scratch. As shown in Figure 5, our method consistently outperforms the supervised baseline by a large margin across different label ratios in both the UCF-101 and HMDB-51 datasets. The performance improvement highlights the efficacy of injecting video representational invariances with our strong data augmentation strategy.

![Fig. 5. Improvement over the supervised baseline.](image)

(a) UCF-101  (b) HMDB-51

Table 5. Comparison with self-supervised learning approaches. The best performance is in bold and the second best is underlined.

| Method                        | Network                  | Kinetics-100 | UCF-101 | HMDB-51 |
|-------------------------------|--------------------------|--------------|---------|---------|
|                               |                          | 20% | 50% | 20% | 10% | 5% | 60% | 50% | 40% |
| VCO (Xu et al., 2019)         | R(2+1)D ResNet-10        | 50.9 | 67.9 | 53.1 | 31.1 | 14.4 | 27.8 | 26.5 | 22.7 |
| DPC (Han et al., 2019)        | R(2+3)D ResNet-18        | 59.2 | 53.1 | 38.9 | 25.3 | 19.2 | 37.2 | 33.2 | 31.6 |
| MemDPC (Han et al., 2020)     | R(2+3)D ResNet-18        | 48.5 | 60.5 | 47.8 | 31.2 | 27.3 | 40.6 | 32.8 | 29.7 |
| Ours                          | 3D ResNet-18             | 61.2 | 59.9 | 51.7 | 40.2 | 27.0 | 38.9 | 38.2 | 32.9 |
| Ours                          | R(2+1)D ResNet-34        | 65.8 | 68.7 | 56.7 | 39.7 | 22.8 | 41.7 | 39.2 | 34.6 |

4.2. Experimental results on contrastive learning-based SSL

In previous sections, we mainly conduct experiments with the consistency-based semi-supervised learning framework, FixMatch (Sohn et al., 2020). In this section, we further validate the effectiveness of strong video data augmentation using a contrastive learning-based method, TCL (Singh et al., 2021).

4.2.1. Experimental setup

**Dataset and evaluation.** Following Singh et al. (2021), we conduct experiments on two large scale action recognition benchmarks: Kinetics-400 (Kay et al., 2017) and Mini-Something-
v2 (Goyal et al., 2017). The Kinetics-400 dataset consists of 240K videos for training and 20K videos for validation across 400 action classes. The Mini-Something-v2 dataset is a subset of the full Something-Something-v2 dataset, containing 81K training videos and 12K testing videos for 87 action classes. Using the same data splits and random seeds as Singh et al. (2021), we conduct three random trials for each label ratio and report the Top-1 accuracy with the standard deviations.

**Compared methods.** We compare our method with the supervised baseline, PseudoLabel (Lee, 2013), MeanTeacher (Tarvainen and Valpola, 2017), S4L (Zhai et al., 2019), MixMatch (Berthelot et al., 2019), FixMatch (Sohn et al., 2020), and the vanilla version of TCL (Singh et al., 2021).

**Implementation details.** We implement our method on top of the publicly available official implementation of TCL. We use the TSM model (Lin et al., 2019) with ResNet-18 (He et al., 2016) as the feature extraction backbone. The vanilla version of TCL contains a fast and a slow branch. The fast branch samples four frames for unlabeled data, and the slow branch samples eight frames from the video. An instance-wise and a group-wise contrastive loss are applied to the data constructed by the two branches. Since the fast branch is a temporal augmentation, we only add the photometric-geometric and ActorCutMix into TCL. With a probability of 50%, we treat the fast sampling data and treated it as the strongly-augmented example. Otherwise, we applied ActorCutMix to the slow sampling data, and treated it as the strongly-augmented example. Lastly, we do not adopt label smoothing for ActorCutMix since TCL uses contrastive objective instead of pseudo-labeling. We use 2 RTX 2080 GPUs to train our models. For other training details such as training schedule and hyper-parameters, we follow the TCL paper (Singh et al., 2021).

4.2.2. Ablation study

Here, we only validate the effectiveness of the photometric-geometric and ActorCutMix operations since the fast pathway in TCL has already imposed a strong augmentation in the temporal axis. We conduct ablation experiments on the 1% label split of both the Kinetics-400 (Kay et al., 2017) and the Mini-Something-v2 (Goyal et al., 2017) datasets using a TSM model with a ResNet-18 backbone. We run the experiments using the first random seed provided by Singh et al. (2021). As shown in Table 6, both photometric-geometric and ActorCutMix augmentations contribute to the performance of both datasets. On the Mini-Something-v2 dataset, ActorCutMix significantly improves performance (+3.34% gain compared to without ActorCutMix) while photometric-geometric augmentation shows a slight improvement of +0.59% compared to temporal augmentation only (TCL). Mini-Something-v2 requires models to rely more on temporal context, compared to Kinetics-400. Therefore, the improvement on the Mini-Something-v2 implies that by injecting scene invariance, our data augmentation encourages the model to leverage the temporal context more effectively than the baseline without ActorCutMix.

| Augmentation | Mini-Something-v2 | Kinetics-400 |
|--------------|------------------|--------------|
| Temporal only (TCL) | 7.92 | 8.16 |
| + Photometric-geometric | 8.51 | 9.00 |
| + ActorCutMix (All) | 11.85 | 9.24 |

4.2.3. Comparison with the state of the arts

We compare our strong data augmentation strategy plugged into TCL to existing methods in Table 7 and Table 8. On the Mini-Something-v2 dataset, our method consistently achieves favorable performance compared with other methods across all label ratios (1%, 5%, and 10%). The results show that the proposed strong augmentation strategy, including ActorCutMix, could improve the performance of a state-of-the-art semi-supervised learning framework. Mini-Something-v2 requires models to rely more on temporal context than Kinetics-400, UCF-101, and HMDB-51. Therefore, the improvement on the Mini-Something-v2 implies that by injecting scene invariance, our data augmentation encourages the model to leverage the temporal context more effectively than TCL. On the Kinetics-400 dataset, we observe a similar trend on the Mini-Something-v2 dataset. Our data augmentation improves upon TCL and achieves state-of-the-art performance on the Kinetics-400 dataset.

| Method | 1% | 5% |
|--------|----|----|
| Supervised | 7.93±0.69 | 16.72±1.17 | 24.67±0.68 |
| PseudoLabel (Lee, 2013) | 6.46±0.32 | 18.76±0.77 | 25.46±0.45 |
| MeanTeacher (Tarvainen and Valpola, 2017) | 7.33±1.13 | 20.23±1.59 | 30.15±0.42 |
| S4L (Zhai et al., 2019) | 7.18±0.97 | 18.58±1.05 | 26.04±1.89 |
| MixMatch (Berthelot et al., 2019) | 7.45±1.01 | 18.63±0.99 | 25.78±1.01 |
| FixMatch (Sohn et al., 2020) | 6.04±0.44 | 21.67±0.18 | 33.38±1.58 |
| * TCL (Singh et al., 2021) | 7.52±0.40 | 29.07±0.71 | 40.09±0.91 |
| Ours | 9.93±1.68 | 31.85±1.32 | 42.82±0.37 |

4.3. Experimental results on fully supervised learning

We demonstrate that our strong data augmentation strategy is general by validating the effectiveness of our strong data augmentation under the fully-supervised (Section 4.3.1) and cross-dataset semi-supervised learning (Section 4.3.2) settings.
4.3.1. Full-label setting results

Our proposed strong data augmentation can further improve supervised training in the full-label setting. We train an R(2+1)D ResNet-34 model from scratch and replace the standard weak video augmentation operations (i.e., random horizontal flip, scaling, cropping) with our strong data augmentation strategy. As shown in Table 9, our strong augmentation leads to a significant performance boost on both the UCF-101 (55.67% → 68.31%) and HMDB-51 (40.78% → 44.51%) datasets.

| Augmentation | UCF-101 | HMDB-51 |
|--------------|---------|---------|
| Standard     | 55.67   | 40.78   |
| Ours         | 68.31   | 44.51   |

4.3.2. Improving Fully-Supervised Learning with Cross-Dataset Semi-Supervised Learning

Lastly, we show that our strong data augmentation strategy can be used in a cross-dataset semi-supervised learning setting to improve the fully-supervised models further. We use the FixMatch framework for these experiments. We use the entire training set of the UCF-101 or HMDB-51 datasets as the labeled set and the Kinetics-100 dataset as the unlabeled set. Since there is no overlap between the labeled and unlabeled data, we modify the semi-supervised framework (as shown in Figure 2) by replacing the standard/weak augmentation in the labeled branch with our strong data augmentation to make sure we generate diverse samples for both labeled and unlabeled data.

As shown in Table 10, our strong augmentation can be used in a cross-dataset setting (high-data regime), leading to a substantial performance gain compared to the fully-supervised training setting with standard/weak data augmentations.

As shown in Table 10, our strong augmentation can be used in a cross-dataset setting (high-data regime), leading to a substantial performance gain compared to the fully-supervised training setting with standard/weak data augmentations.

| Data          | UCF-101 | HMDB-51 |
|---------------|---------|---------|
| Standard      | 55.67   | 40.78   |
| Ours          | 68.31   | 44.51   |

5. Conclusions

In this paper, we investigate different types of data augmentation strategies for video action recognition, in both low-label and full-label settings. Our study shows the importance of (1) temporally-coherent photometric and geometric augmentations, (2) temporal augmentations, and (3) actor/scene augmentation. We show promising action recognition performance on all the public benchmarks in both low-label and full-label settings with all the augmentations. We believe that our exploration help facilitate future video action recognition research.

CRediT authorship contribution statement

Yuliang Zou: Conceptualization, Methodology, Software, Writing - original draft. Jinwoo Choi: Conceptualization, Methodology, Software, Writing - original draft, Supervision. Qitong Wang: Software, Writing - original draft. Jia-Bin Huang: Writing – original draft, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This work was supported in part by NSF under Grant No. 1755785 and by a grant from Kyung Hee University in 2021 (KHU-20210735) and by the Institute of Information and Communications Technology Planning and Evaluation (IITP) grant funded by the Korea Government (MSIT) (Artificial Intelligence Innovation Hub) under Grant 2021-0-02068.

References

Arnab, A., Dehghani, M., Heigold, G., Sun, C., Łańcūć, M., Schmid, C., 2021. Vivit: A video vision transformer, in: ICCV.
Bachman, P., Alsharif, O., Precup, D., 2014. Learning with pseudo-ensembles, in: NeurIPS.
Bahng, H., Chun, S., Yun, S., Choo, J., Oh, S.J., 2020. Learning de-biased representations with biased representations, in: ICML.
Benaim, S., Ephrat, A., Lang, O., Mosseri, I., Freeman, W.T., Rubinstein, M., Irani, M., Dekel, T., 2020. Speednet: Learning the speediness in videos, in: CVPR.
Berthelot, D., Carlini, N., Cubuk, E.D., Kurakin, A., Sohn, K., Zhang, H., Raffel, C., 2020. Remixmatch: Semi-supervised learning with distribution matching and augmentation anchoring, in: ICLR.
Berthelot, D., Carlini, N., Goodfellow, I., Papernot, N., Oliver, A., Raffel, C.A., 2019. Mixmatch: A holistic approach to semi-supervised learning, in: NeurIPS.
Carreira, J., Zisserman, A., 2017. Quo vadis, action recognition? a new model and the kinetics dataset, in: CVPR.
Chen, T., Kornblith, S., Norouzi, M., Hinton, G., 2020a. A simple framework for contrastive learning of visual representations, in: ICLR.
Chen, X., Fan, H., Girshick, R., He, K., 2020b. Improved baselines with momentum contrastive learning. arXiv preprint arXiv:2003.04297.
Choi, J., Gao, C., Messou, J.C., Huang, J.B., 2019. Why can’t i dance in the mall? learning to mitigate scene bias in action recognition, in: NeurIPS.
Contributors, M., 2020. Openmmlab’s next generation video understanding toolbox and benchmark. https://github.com/open-mmlab/mmaction2.
Cubuk, E.D., Zoph, B., Mane, D., Vasudevan, V., Le, Q.V., 2019. Autoaugment: Learning augmentation policies from data, in: CVPR.
Cubuk, E.D., Zoph, B., Shlens, J., Le, Q.V., 2020. Randaugment: Practical automated data augmentation with a reduced search space, in: CVPR Workshops.
DeVries, T., Taylor, G.W., 2017. Improved regularization of convolutional neural networks with cutout. arXiv preprint arXiv:1708.04552.
Epstein, D., Chen, B., Vondrick, C., 2020. Oops! predicting unintentional action in video, in: CVPR.
Fabian Caba Heilbron, Victor Escorcia, B.G., Niebles, J.C., 2015. Activitynet: A large-scale video benchmark for human activity understanding, in: CVPR.
Fan, H., Xiong, B., Mangalam, K., Li, Y., Yan, Z., Malik, J., Feichtenhofer, C., 2021. Multiscale vision transformers, in: ICCV.
Feichtenhofer, C., 2020. X3d: Expanding architectures for efficient video recognition, in: CVPR.
Feichtenhofer, C., Fan, H., Malik, J., He, K., 2019. Slowfast networks for video recognition, in: ICCV.
Feichtenhofer, C., Pinz, A., Zisserman, A., 2016. Convolutional two-stream network fusion for video action recognition, in: CVPR.
Geirhos, R., Rubisch, P., Michaelis, C., Bethge, M., Wichmann, F.A., Brendel, W., 2018. Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness, in: ICLR.
Gidaris, S., Singh, P., Komodakis, N., 2018. Unsupervised representation learning by predicting image rotations, in: ICLR.
| Supervised (Standard Augmentation) | UCF-101 | - | 55.67 | Reference |
|-----------------------------------|---------|----|------|-----------|
| Supervised (Our Strong Augmentation) | UCF-101 | - | 68.31 | +12.64 |
| Cross-Dataset Semi-Supervised | UCF-101 | Kinetics-100 | 70.31 | +14.64 |

| Supervised (Standard Augmentation) | HMDB-51 | - | 40.78 | Reference |
|-----------------------------------|---------|----|------|-----------|
| Supervised (Our Strong Augmentation) | HMDB-51 | - | 44.51 | +3.73 |
| Cross-Dataset Semi-Supervised | HMDB-51 | Kinetics-100 | 45.75 | +4.97 |

Table 10. Cross-dataset semi-supervised learning. We train R(2+1)D ResNet-34 models from scratch.
for action recognition, in: CVPR.
Yang, Y., Loquercio, A., Scaramuzza, D., Soatto, S., 2019. Unsupervised moving object detection via contextual information separation, in: CVPR.
Yoo, J., Ahn, N., Sohn, K.A., 2020. Rethinking data augmentation for image super-resolution: A comprehensive analysis and a new strategy, in: CVPR.
Yun, S., Han, D., Oh, S.J., Chun, S., Choe, J., Yoo, Y., 2019. Cutmix: Regularization strategy to train strong classifiers with localizable features, in: ICCV.
Yun, S., Oh, S.J., Heo, B., Han, D., Kim, J., 2020. Videomix: Rethinking data augmentation for video classification. arXiv preprint arXiv:2012.03457.
Zhai, X., Oliver, A., Kolesnikov, A., Beyer, L., 2019. S4l: Self-supervised semi-supervised learning, in: ICCV.
Zhang, Y., Jia, G., Chen, L., Zhang, M., Yong, J., 2020. Self-paced video data augmentation by generative adversarial networks with insufficient samples, in: ACM MM.
Fig. 6. **Class accuracy.** We compare per-class accuracies of the supervised baseline and the semi-supervised model with (a) temporal augmentations only, (b) ActorCutMix augmentation only, and (c) our final all augmentations on the 20% label split of the UCF-101. Classes are sorted in ascending order of the supervised baseline accuracy. Best viewed with zoom and color.
Fig. 7. Visual examples showing the improvement over the supervised baseline. UCF-101 examples misclassified by the baseline but are correctly classified with the proposed augmentations. Correct/incorrect predictions are shown in green/red.