Iterative Contrast-Classify For Semi-supervised Temporal Action Segmentation

Dipika Singania, Rahul Rahaman, Angela Yao

National University of Singapore
dipika16@comp.nus.edu.sg, rahul.rahaman@u.nus.edu, ayao@comp.nus.edu.sg

Abstract

Temporal action segmentation classifies the action of each frame in (long) video sequences. Due to the high cost of frame-wise labeling, we propose the first semi-supervised method for temporal action segmentation. Our method hinges on unsupervised representation learning, which, for temporal action segmentation, poses unique challenges. Actions in untrimmed videos vary in length and have unknown labels and start/end times. Ordering of actions across videos may also vary. We propose a novel way to learn frame-wise representations from temporal convolutional networks (TCNs) by clustering input features with added time-proximity condition and multi-resolution similarity. By merging representation learning with conventional supervised learning, we develop an “Iterative-Contrast-Classify (ICC)” semi-supervised learning scheme. With more labelled data, ICC progressively improves in performance; ICC semi-supervised learning, with 40% labelled videos, performs similar to fully-supervised counterparts. Our ICC improves MoF by \{+1.8, +5.6, +2.5\}\% on Breakfast, 50Salads and GTEA respectively for 100% labelled videos.

1 Introduction

Temporal action segmentation takes long untrimmed video containing multiple actions in a sequence and estimates the action labels for each video frame. There is a huge annotation cost to label each frame of all videos for action segmentation, especially as the videos are minutes long. Several works aim to reduce annotation requirements with weak supervision like transcripts (Chang et al. 2019), or few frame labels (Li, Farha, and Gall 2021). In this work, we advocate using semi-supervised learning, *i.e.* having labels only for a fraction of the videos in the training set. Specifically, we design the unsupervised representation learning step to learn the underlying distribution of all unlabelled videos, which helps achieve higher temporal action segmentation scores with very few labeled videos in the subsequent supervised training step.

For unsupervised representation learning, we are inspired by the success of contrastive learning in images (Chen et al. 2020b), short-trimmed videos (Lorre et al. 2020, Singh et al. 2021) and other areas of machine learning (Chen et al. 2021, Rahaman, Ghosh, and Thiery 2021). Works which apply contrastive learning to longer sequences bring together multiple viewpoints of a sequence (Sermanet et al. 2018) or multiple modalities, such as video and text (Alwassel et al. 2019) or video and audio (Miech et al. 2020). These settings target multi-view or multi-modal representations and are not applicable for videos in action segmentation datasets. Also, standard contrastive technique to bring image (or video) and its augmentations near is unlikely to be effective. Action segmentation is a frame-wise (and not video-wise) classification task so a model should capture similarities across temporally disjoint but semantically similar frames, while factoring temporal continuity within every action segment. The latter is easy to incorporate in the form of temporal constraints, but the former poses significant challenges without action labels.

As such, contrastive learning has not yet been explored for action segmentation and our work is the first. We design a novel strategy to form the positive and negative sets without labels by leveraging the discriminativeness of the pre-trained I3D (Carreira and Zisserman 2017) input features (see Fig. 2 right). As a base model, we use a SOTA temporal convolutional network (TCN) (Singhania, Rahaman, and Yao 2021), a key advantage is the progressive temporal upsampling in the decoder which allows us to integrate contrastive learning to multiple temporal resolutions and enforce temporal continuity by design. Our proposed multi-resolution representation for contrastive learning is previously unexplored and is highly effective for temporal action segmentation.

Equipped with our (unsupervised) learned model, we can...
perform semi-supervised learning with only a small fraction
of labelled training videos. To fully utilize the labeled and
unlabeled dataset, we propose a novel Iterative-Contrast-
Classify algorithm that updates the representations while
learning to segment sequences and assigning pseudo-labels to
the unlabeled videos. We achieve noteworthy segmentation
performance with just 5% labelled videos, while with 40% labels, we can almost match the full-supervision (see Fig. 1).

To the best of our knowledge, our work is the first to apply
semi-supervised learning for temporal action segmentation.
The closest in spirit are SSTDA (Chen et al. 2020a), TSS (Li
Farha, and Gall 2021). However, these works are weakly-
supervised setups and require (weak) labels for every training
video (see Fig. 2 left). TSS require one frame label for each action. While the percentage of overall labeled frames is
very little (0.03%), the annotation effort should not be under-
estimated. Annotators must still watch all the videos and
labelling timestamp frames gives only a 6X speedup com-
pared to densely labelling all frames (Ma et al. 2020).

Summarizing our contributions, we:

• Proposed a novel unsupervised representation learning
that leverages the discriminativeness in pre-trained input
features and temporal continuity in a video sequence.

• Designed a multi-resolution representation for contrastive learning which inherently encodes sequence variations
and temporal continuity.

• Formulated a new semi-supervised learning variant of
temporal action segmentation and proposed an “Iterative-
Contrast-Classify (ICC)” algorithm that iteratively fine-
tunes representations and strengthens segmentation per-
formance with few labelled videos.

2 Related Work

Temporal action segmentation Classifying and tempo-
rally segmenting fine grained actions in long video requires
both local motion and global long-range dependencies in-
formation. It is standard to extract snippet level IDT (Wang
and Schmid 2013) or I3D features to capture local temporal
motion (and to reduce computational expense of joint end-
to-end training). These features are used as inputs to Tem-

oral Convolution Networks (TCNs) which captures global
action compositions, segment durations and long-range de-
pendencies (see Fig 2 right). Fully supervised frameworks
require per-frame annotations of all the video sequences in
the dataset. Popular TCN frameworks include U-Net style
encoder-decoders (Lea et al. 2017; Lei and Todorovic 2018;
Singhania, Rahaman, and Yao 2021) or temporal resolution
preserving MSTCNs (Li et al. 2020; Farha and Gall 2019).

Weakly supervised methods bypass per-frame annotations
and use labels such as ordered lists of actions (Ding and
Xu 2018; Richard et al. 2018; Chang et al. 2019; Li, Lei,
and Todorovic 2019; Souri et al. 2019) or a small percentage
of action time-stamps (Kuehne, Richard, and Gall 2018; Li,
Farha, and Gall 2021; Chen et al. 2020a) for all videos.

Unsupervised approaches use clustering, including k-
means (Kukleva et al. 2019), agglomerative (Sarfraz et al.
2021), and discriminative clustering (Sener and Yao 2018).
To improve clustering performance, some works (Kukleva
et al. 2019; VidalMata et al. 2021) learns representation by
predicting frame-wise feature’s absolute temporal positions
in the video. Our unsupervised representation implicitly cap-
ture relative temporal relationships based on temporal dis-
tance rather than absolute positions.

Unsupervised Contrastive Feature Learning dates back
to (Hadsell, Chopra, and LeCun 2006) but was more re-
cently formalized in SimCLR (Chen et al. 2020b). Most
works (Chen et al. 2021; Rahaman, Ghosh, and Thiery 2021;
He et al. 2020; Khosla et al. 2020) hinge on well-defined data
augmentations, with the goal of bringing together the original
and augmented sample in the feature space.

The few direct extensions of SimCLR for video (Bai
et al. 2020; Qian et al. 2020; Lorre et al. 2020) target action
recognition on few seconds short clips. Others integrate
contrastive learning by bringing together next-frame feature
predictions with actual representations (Kong et al. 2020;
Lorre et al. 2020), using path-object tracks for bringing cycle-
consistency (Wang, Zhou, and Li 2020), and considering
multiple viewpoints (Sermanet et al. 2018) or accompanying
modalities like audio (Alwassel et al. 2019) or text (Miech
et al. 2020). We are inspired by these works to develop con-
trastive learning for long-range segmentation. However, pre-
vious works differ fundamentally in both aim i.e. learning the
underlying distribution of cycle-consistency in short clips,
and input data e.g. multiple viewpoints or modalities.
3 Preliminaries

Definitions: We denote a video as $V \in \mathbb{R}^{T \times F}$; for each temporal location $t < T$, frame $V[t] \in \mathbb{R}^F$ is a $F$-dimensional pre-trained I3D feature. Note, input I3D feature is from model pre-trained on Kinetics dataset (Carreira and Zisserman 2017) and is not fine-tuned on our segmentation datasets.

For simplicity, unless otherwise explicitly noted, e.g. in Section 4.3 we treat the temporal dimension of all the videos as a normalized unit interval $t \in [0, 1]$, i.e. $T = 1$. Each frame $V[t]$ has a ground truth action label $y[t] \in \{1, ..., A\}$ from a pre-defined set of $A$ action classes. Additionally, each video has a higher-level complex activity label $c \in \{1, ..., C\}$. The complex activity specifies an underlying objective, e.g. ‘making coffee’ for action sequence {‘take cup’, ‘pour coffee’, ‘add sugar’, ‘stir’}, though the sequence ordering may differ e.g. ‘add sugar’ may come before ‘pour coffee’.

Base Segmentation Model: We use the C2F-TCN (Singhania, Rahaman, and Yao 2021), which is a U-Net style encoder-decoder, though our method is also applicable to other base models such as the ED-TCN (Lea et al. 2017). The encoder layers $\Phi$ take pre-trained video features as inputs and progressively increases the feature abstraction while reducing the temporal resolution up to some bottleneck $\Gamma$. The decoder layers $\Psi$ then increase the temporal resolution symmetrically with respect to the encoder. We refer to the Appendix B.1 or to (Singhania, Rahaman, and Yao 2021) for more details.

The overall encoder-decoder $M := (\Phi : \Gamma : \Psi)$ takes $V$ as input and produces output frame-wise features $f = M(V)$. For each time $t$, $f[t] \in \mathbb{R}^d$ is a $d$-dimensional representation. We describe in detail how $f$ is formed in Section 4.3.

Learning Framework & Data Split: Our overall framework has two stages. First, we apply an unsupervised representation learning to learn a model $M$ (Section 5). Subsequently, model $M$ is trained with linear projection layers (action classifiers) with a small portion of the labelled training data to produce the semi-supervised model $(M : G)$ (Section 5). For representation learning, we follow the convention of previous unsupervised works (Kukleva et al. 2019; VidalMata et al. 2021) in which actions $y$ are unknown, but the complex activity of each video is known. For the semi-supervised stage, we use the ground truth $y$ for a small subset of labelled video $D_L$ out of a larger training dataset $D = D_U \cup D_L$, where $D_U$ denotes the unlabelled videos.

Contrastive Learning: We use contrastive learning for our unsupervised frame-wise representation learning. Following the formalism of (Chen et al. 2020b), we define a set of features $F := \{f_i, i \in I\}$ indexed by a set $I$. Each feature $f_i \in F$ is associated with two disjoint sets of indices $P_i \subset I \setminus \{i\}$ and $N_i \subset I \setminus \{i\}$. The features in the positive set $P_i$ should be similar to $f_i$, while the features in the negative set $N_i$ should be contrasted with $f_i$. For each $j \in P_i$, the contrastive probability $p_{ij}$ is defined as:

$$p_{ij} = \frac{e_{\tau}(f_i, f_j)}{e_{\tau}(f_i, f_j) + \sum_{k \in N_i} e_{\tau}(f_i, f_k)},$$

where the term $e_{\tau} = \exp(\cos(f_i, f_j)/\tau)$ is the exponential of the cosine similarity between $f_i$ and $f_j$, scaled by temperature $\tau$. Maximizing the probability in Eq. (1) ensures that $f_i, f_j$ are similar while also decreasing the cosine similarity between $f_i$ and any feature in the negative set. The key to effective contrastive learning is to identify the relevant positive and negative sets to perform the targeted task.

4 Unsupervised Representation Learning

Our representation learning applies contrastive learning at frame-level, based on input feature clustering and temporal continuity (Sec. 4.1), and at a video-level, by leveraging the complex activity labels (Sec. 4.2). We merge the two objectives into a common loss that is applied to our multi-temporal resolution feature representations (Sec. 4.3).
4.1 Frame-Level Contrastive Formulation

Input Clustering: Our construction of positive and negative sets should respect the distinction between different action classes. But as our setting is unsupervised, there are no labels to guide the formation of these sets. Hence we propose to leverage the discriminative properties of the pre-trained input I3D features to initialize the positive and negative sets. Note that while the clusters are formed on the input features, our contrastive learning is done over the representation $f$ produced by the C2F-TCN model (yellow panel of Fig.3).

Specifically, we cluster the individual frame-wise inputs $V[t]$ for all the videos within a small batch. We use k-means clustering and set the number of clusters as $2A$ (ablations in Appendix-A.1), i.e. twice the number of actions to allow variability even within the same action. After clustering, each frame $t$ is assigned the cluster label $l[t] \in \{1, \ldots, 2A\}$. Note that this simple clustering does not require videos of the same (or different) complex activities to appear in a mini-batch. It also does not incorporate temporal information – this differs from previous unsupervised works (Kukleva et al. 2019; VidalMata et al. 2021) that embed absolute temporal locations into the input features before clustering.

Representation Sampling Strategy: The videos used for action segmentation are long, i.e. 1-18k frames. Constraining all the frames of every video in a batch would be too computationally expensive to consider, whereas contrastive loss of even a few representation back-propagates through the entire hierarchical TCN. To this end, we dynamically sample a fixed number of frames from each video to form the feature (representation) set $F$ for each batch of videos. Note that the sampling is applied to the feature representations $f = M(V)$ and not to the inputs $V$; and the full input $V$ is required to pass through the TCN to generate $f$.

Let $I$ denote the feature set index (as in sec[3]) and for any feature index $(n, i) \in I$, let $n$ denote the video-id and $i$ the sample-id within that video. For a video $V_n$ and a fixed $K > 0$, we sample $2K$ frames among the cluster labels $l[t] \in \{1, \ldots, 2A\}$ and obtain the feature set $F_n := \{f_n[l[t]] : i \leq 2K\}$. To do so, we divide the unit interval $[0, 1]$ into $K$ equal partitions and randomly choose a single frame from each partition. Another $K$ frames are then randomly chosen away ($\varepsilon < 1/K$) from each of the first $K$ samples. This strategy ensures diversity (the first $K$ samples) while having nearby $\varepsilon-$distanced features (the second $K$ samples) to either enforce temporal continuity if they are the same action, or learn boundaries if they are different actions (approximated by the cluster labels $l$ when actions labels are unknown).

Frame-level positive and negative sets: Constructing the positive and negative set for each index $(n, i) \in I$ requires a notion of similar features. The complex activity label is a strong cue, as there are either few or no shared actions across the different complex activities. For video $V_n$ with complex activity $c_n$, we contrast index $(m, j)$ with $(n, i)$ if $c_m \neq c_n$. In datasets without meaningful complex activities (50Salads, GTEA), this condition is not applicable.

The cluster labels $l$ of the input features already provides some separation between actions (see Table[1]); we impose an additional temporal proximity condition to minimize the possibility of different action in the same cluster. Formally, we bring the representation with index $(n, i)$ close to $(m, j)$ if their cluster labels are same i.e $l_n[l[t^n_i]] = l_m[l[t^m_j]]$ and if they are close-by in time, i.e., $|t^n_i - t^m_j| < \delta$. For datasets with significant variations on the action sequence, e.g. 50Salads, the same action may occur at very different parts of the video so we choose higher $\delta$, vs. smaller $\delta$ for actions that follow more regular ordering, e.g. Breakfast. Sampled features belonging to the same cluster but exceeding the temporal proximity, i.e. $l_n[l[t^n_i]] = l_m[l[t^m_j]]$ but $|t^n_i - t^m_j| > \delta$ are not considered for neither the positive nor the negative set.

Putting together the criteria from complex activity labels, clustering and temporal proximity, our positive and negative sets for index $(n, i)$, i.e. sample $i$ from video $n$ is defined as $P_{n,i} = \{(m, j) : c_m = c_n, |t^n_i - t^m_j| < \delta, l_n[l[t^n_i]] = l_m[l[t^m_j]]\}$

and $N_{n,i} = \{(m, j) : c_m \neq c_n \} \cup \{(m, j) : c_m = c_n, l_n[l[t^n_i]] \neq l_m[l[t^m_j]]\}$

where $m, n$ are video indices, $t^n_i$ is the frame-id corresponding to the $i^{th}$ sample of video $n$, $c_n$ is the complex activity of video $n$, and $l_n[l[t^n_i]]$ the cluster label of frame $t^n_i$. For an index $(m, j) \in P_{n,i}$, i.e. belonging to the positive set of $(n, i)$, the contrastive probability becomes

$$p_{ij}^m = \frac{e^\tau(f_n[t^n_i], f_m[t^m_j])}{e^{\tau}(f_n[t^n_i], f_m[t^m_j]) + \sum_{(r,k) \in N_{n,i}} e^{\tau}(f_n[t^n_i], f_r[t^r_k])}.$$ (3)

where $e^\tau$ is the $\tau$-scaled exponential cosine similarity of Eq. (1). For feature representations $f_n[t^n_i]$, Fig.3 visualizes the positive set with pull-together green-arrows and negative set with push apart red-arrows.

4.2 Video-Level Contrastive Formulation

To further emphasize global differences between different complex activities, we construct video-level summary features $h_n \in \mathbb{R}^{N_{video} \times d}$ by max-pooling the frame-level features $f_n \in \mathbb{R}^{t \times n \times d}$ along the temporal dimension. For video $V_n$, we define video-level feature $h_n = \max_{1 \leq t \leq T} f_n(t)$. Intuitively, the max-pooling captures permutation-invariant features and has been effective for aggregating video segments (Sener, Singhania, and Yao 2020). With features $h_n$, we formulate a video-level contrastive learning. Reusing the index set as video-ids, $I = \{1, \ldots, |\mathcal{D}|\}$, we define a feature set $\mathcal{F} := \{h_n : n \leq |\mathcal{D}|\}$, where for each video $n$, there is a positive set $\mathcal{P}_n := \{m : c_m = c_n\}$ and a negative set as $\mathcal{N}_n = I \setminus \mathcal{P}_n$. For video $n$ and another video $m \in \mathcal{P}_n$ in its positive set, the contrastive probability can be defined as

$$p_{nm} = \frac{e^\tau(h_n, h_m)}{e^\tau(h_n, h_m) + \sum_{r \in \mathcal{N}_n} e^\tau(h_n, h_r).}.$$ (4)

For our final unsupervised representation learning we use contrastive loss function $\mathcal{L}_{con}$ that sums the video-level and frame-level contrastive losses:

$$\mathcal{L}_{con} = -\frac{1}{N_1} \sum_{n \in \mathcal{P}_n} \sum_{m \in \mathcal{P}_n} \log p_{nm} - \frac{1}{N_1} \sum_{n \in \mathcal{P}_n} \sum_{m,j \in \mathcal{P}_n} \log p_{ij}^m,$$ (5)

where $N_1 = \sum_{n} |\mathcal{P}_n|$, $N_2 = \sum_{m,j \in \mathcal{P}_n}$ and $p_{ij}^m, p_{nm}$ are as defined in equation (3) and (4) respectively. In practice, we compute this loss over mini-batches of videos.
4.3 Multi-Resolution Representation

We in this work show that constructing an appropriate representation can boost the performance of contrastive learning significantly. For this subsection, we switch to an absolute integer temporal index, i.e. for a video V the frame indices are \( t \in \{1, \ldots, T\} \) where \( T \geq 1 \). The decoder \( \Psi \) has six layers; each layer producing features \( z_u, 1 \leq u \leq 6 \) while progressively doubling the temporal resolution, i.e. the length of \( z_u \) is \( [T/2^{6-u}] \). The temporally coarser features provide more global sequence-level information while the temporally fine-grained features contain more local information.

To leverage the full range of resolutions, we combine \( \{z_1, \ldots, z_6\} \) into a new feature \( \hat{z} \). Specifically, we upsample each decoder feature \( z_u \) to \( \hat{z}_u := \text{up}(z_u, T) \) having a common length \( T \) using a temporal up-sampling function \( \text{up}(\cdot, T) \) such as ‘nearest’ or ‘linear’ interpolation. The final frame-level representation for frame \( t \) is defined as \( f[t] = (\hat{z}_1[t] ; \hat{z}_2[t] ; \ldots ; \hat{z}_6[t]) \), where \( \hat{z}_u[t] = \hat{z}_u[t]/ \| \hat{z}_u[t] \| \), i.e. \( \hat{z}_u[t] \) is normalized and then concatenated along the latent dimension for each \( t \) (see Fig. 3). It immediately follows that for frames \( 1 \leq s, t \leq T \), the cosine similarity \( \cos(\cdot) \) can be expressed as

\[
\cos(f[t], f[s]) = \sum_{u=1}^{6} \omega_u \cdot \cos(z_u[t], z_u[s]). \tag{6}
\]

As a result of our construction, the weights in Eq. (6) becomes \( \omega_u = \frac{1}{6} \), i.e. each decoder layer an equal contribution in the cosine-similarity. Normalizing after concatenation, would cause Eq. (3)’s coefficients \( \omega_u \propto \| z_u[t] \| \cdot \| z_u[s] \| \). The importance of this ordering is verified in Appendix-C.

Advantages: Our representation \( f \) encodes some degree of temporal continuity implicitly by design. For example, in the case of ‘nearest’ up-sampling, it can be shown that for frames \( 1 \leq s, t \leq T \), if \( \lfloor t/2^u \rfloor = \lfloor s/2^u \rfloor \) for some integer \( u \), then it implies that \( \sin(f[t], f[s]) \geq 1 - u/3 \) (detailed derivation in Appendix-C). Including temporally coarse features like \( z_6 \) and \( z_1 \) allows the finer-grained local features \( z_6 \) to disagree with nearby frames without harming the temporal continuity. This makes the learned representations less prone to the common occurring problem of over-segmentation (Wang et al. 2020). This is demonstrated by the significant improvement in edit, F1 scores in the last row of Table 1.

4.4 Evaluating the Learned Representation

To evaluate the learned representations, we train a simple linear classifier \( G_f \) on \( f \) to classify frame-wise action labels. This form of evaluation is directly in line other works on unsupervised representation learning (Feichtenhofer et al. 2021; Chen et al. 2020; Caron et al. 2021). The assumption is that if the unsupervised learned features are sufficiently strong, then a simple linear classifier is sufficient to separate the action classes. Note that while our representation learning is unsupervised, learning the classifier \( G_f \) is fully-supervised, using ground truth labels \( y \) with a cross-entropy loss \( L_{ce} \) over the standard splits of the respective datasets.

5 Semi-Supervised Temporal Segmentation

After unsupervised representation learning, the model \( M \) cannot yet be applied for action segmentation. The decoder output must be coupled with a linear projection \( G \) and a soft-max to generate the actual segmentation. \( G \) can only be learned using labels, i.e. from \( D_L \), though the labels can be further leveraged to fine-tune \( M \) (Sec. 5.1). Afterwards, \( M \) and \( G \) can be applied to unlabelled data \( D_U \) to generate pseudo-labels. The pooled set of labels from \( D_L \cup D_U \) can then be applied to update the representations in \( M \) (Sec. 5.2). By cycling between these updates, we propose an Iterative-Contrast-Classify (ICC) algorithm (Sec. 5.3) that performs semi-supervised action segmentation (see overview in Fig. 4).

5.1 Classify Step: Learning \( G, M \) with \( D_L \)

Similar to the supervised C2F-TCN, each decoder layer’s representations \( z_u \) (temporal dim \( [T/2^{6-u}] \)) is projected with a linear layer \( G_u \) to \( A \)-dimensional vector where \( A \) is the number of action classes. This is followed by a softmax to obtain class probabilities \( p_u \) and a linear interpolation in time to up-sample back to the input length \( T \). For frame \( t \), the prediction \( p[t] \) is a weighted ensemble of up-sampled \( p_u \), i.e. \( p[t] = \sum u \alpha_u \text{up}(p_u, T) \) where \( \alpha_u \) is the ensemble weight of decoder \( u \) with \( \sum \alpha_u = 1 \), and \( \text{up}(p_u, T) \) denotes the upsampled decoder output of length \( T \). The sum is action-wise and the final predicted action label is \( \hat{y}_t = \arg \max_k A \cdot p[t, k] \). Note that \( G := \{G_u\} \) differs from the linear classifier \( G_f \) of Sec. 4.3. \( G_f \) is applied to the representation \( f \) used for the contrastive learning (see Sec. 4.3), whereas \( \{G_u\} \) are applied individually to different \( z_u \).

In addition to learning \( G, D_L \) can be leveraged to fine-tune \( M \) as well. In Eq. (2), the positive and negative sets \( P_{n,i} \) and \( N_{n,i} \) can be modified for \( D_L \) to use the ground truth labels by replacing the unsupervised cluster labels \( l_n[t_i] \) with ground truth action labels \( y_n[t_i] \). Note that the learning rate used for fine-tuning the parameters of the model \( M \) is
We test on Breakfast Actions (Kuehne, Arslan, and Serre 2014) (1.7K videos, 10 complex activities, 48 actions), 50Salads (Stein and McKenna 2013) (50 videos, 19 actions) and GTEA (Fathi, Ren, and Rehg 2011) (28 videos, 11 actions). The standard evaluation criteria are the Mean-over-Frames (MoF), segment-wise edit distance (Edit), and F1-scores with IoU thresholds of 0.10, 0.25 and 0.50 (F1@[10, 25, 50]). We report results with the stronger I3D input features and make comparisons with IDT features in Appendix-D.

We use the specified train-test splits for each dataset and randomly select 5% or 10% of videos from the training split for labelled dataset D_L. As GTEA and 50Salads are small, we use 3 and 5 videos as 5% and 10% respectively to incorporate all A actions. We report mean and standard deviation of five different selections. For unsupervised representation learning, we use all the unlabelled videos in the dataset which applies cluster labels condition in Eq. (2). The ‘Cluster’ row in Table 1 breaks down the contributions from Eq. (2).

The pseudo labels for D_U are significantly better representative of the (unseen) action labels than the clusters obtained from the input I3D features used in the unsupervised stage. Thus we can improve our contrastive representation by using the pseudo labels (obtained after classify) for another contrast step. This refined representation in turn can help in finding better pseudo labels through another following classify step. By iterating between the contrast and classify steps, we can progressively improve the performance of the semi-supervised segmentation. The segmentation performance is evaluated at the end of the classify step after the training of G. We denote the combined model of M and G for each iteration i as ICC_i. In this way, initial unsupervised representation learning can be considered the “contrast” step of ICC_1, where cluster labels are used instead of pseudo-labels. We found that performance saturates after 4 iterations of contrast-classify and refer to the performance of ICC_4 as our final semi-supervised result.

6 Experiments

6.1 Datasets, Evaluation, Implementation Details

We test on Breakfast Actions (Kuehne, Arslan, and Serre 2014) (1.7K videos, 10 complex activities, 48 actions), 50Salads (Stein and McKenna 2013) (50 videos, 19 actions) and GTEA (Fathi, Ren, and Rehg 2011) (28 videos, 11 actions). The standard evaluation criteria are the Mean-over-Frames (MoF), segment-wise edit distance (Edit), and F1-scores with IoU thresholds of 0.10, 0.25 and 0.50 (F1@[10, 25, 50]). We report results with the stronger I3D input features and make comparisons with IDT features in Appendix-D.

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6.2 Evaluation of Representation Learning

Linear Classification Accuracy of our unsupervised representation learning (see Sec. 4.4) is shown in Table I. In the first green section, we evaluate the input I3D features with a linear classifier to serve as a baseline. Our representation has significant gains over the input I3D, verifying the ability of the base TCN to perform the task of segmentation with our designed unsupervised learning.

Frame- and Video-Level Contrastive Learning: The blue section of Table I breaks down the contributions from Sec. 4.1 and 4.2 when forming the positive and negative sets of contrastive learning from Eq. 2. The ‘Cluster’ row applies cluster labels condition i.e. $l_n[t_i^n] = l_m[t_m^n]$ and ‘(+Proximity)’ adds the condition $|t_i^n - t_m^n| < \delta$. Adding time proximity is more effective for Breakfast and GTEA likely because their videos follows a more rigid sequencing than 50Salads. Adding the Video-Level contrastive loss from Sec. 4.2 in Breakfast gives further boosts.

Multi-Resolution Representation: The orange section of Table I verifies that our multi-resolution representation f (see Table 1: Component-wise analysis of the unsupervised representation learning framework with a linear classifier.
Sec. (3.3) outperforms the use of only the final decoder layer feature $z_6$. Gains are especially notable for the F1-score and Edit-distance, verifying that f has less over-segmentation.

No Initial Representation Learning: Although model M is continually updated during the ICC, Appendix-D.2 shows that the initial unsupervised representation learning is critical. Bypassing this step in the first iteration of ICC and going straight to classify step results in a gap of $\geq 10\%$ F1.

6.3 Evaluation of Semi-Supervised Learning

ICC Components: The orange section of Table 2 shows the progressive improvements as we increase the number of iterations of our proposed ICC algorithm. The gain in performance is especially noticeable for Edit and F1 scores. Segmentation result reported are after the classify step. Improvements gained by updating the feature representation after the contrast step but before classify of the next iteration is shown in the Appendix-D.3.

Additional Ablations: Due to lack of space, we refer the reader to Appendix-B. Notably, we demonstrate ICC results with alternative base model ED-TCN (Lea et al. 2017) and draw difference to using MS-TCN (Li et al. 2020).

Semi-Supervised vs Supervised: The green and blue sections of Table 2 shows our final ‘Semi-Super’ results, i.e. ICC1 for various percentages of labelled data. We compare with the ‘Supervised’ case of training the base model C2F-TCN with the same labelled dataset $D_L$; for fairness, $100\%$ C2F-TCN results is reported without test-time augmentations and action loss. ICC significantly outperforms the supervised baseline in all the metrics (see also Fig. 1) for all amounts of training data, including $100\%$.

In fact, with just 5$%$ of labelled videos, we are only 8$\%$ less in MoF in Breakfast actions compared to fully-supervised (100$\%$). Using less than 5$\%$ (3 videos for 50salads and GTEA) of training videos makes it difficult to ensure coverage of all the actions.

Table 2: Our final all metrics evaluation of proposed ICC algorithm on 3 benchmark action segmentation datasets.

| $D_L$ | Method | Breakfast | $P1@\{10,25,50\}$ | Edit | MoF | $P1@\{10,25,50\}$ | Edit | MoF | $P1@\{10,25,50\}$ | Edit | MoF |
|-------|--------|-----------|-------------------|-------|-----|-------------------|-------|-----|-------------------|-------|-----|
| $\approx 5$ | ICC1          | 54.5       | 48.7              | 33.3  | 54.6 | 64.2              | 41.3  | 37.2 | 27.8            | 35.4  | 57.3 |
|       | ICC2          | 56.9       | 51.9              | 34.8  | 56.5 | 65.4              | 45.7  | 40.9 | 30.7            | 40.9  | 59.5 |
|       | ICC3          | 59.9       | 53.3              | 35.5  | 56.3 | 64.2              | 50.1  | 46.7 | 35.3            | 43.7  | 60.9 |
|       | ICC4          | 60.2       | 53.5              | 35.6  | 56.6 | 65.3              | 52.9  | 49.0 | 36.6            | 45.6  | 61.3 |
|       | Gain          |            | 5.7               | 4.8   | 2.3  | 2.0               | 1.1   | 1.6 | 1.5             | 11.0  | 8.8 |

| $\approx 10$ | Supervised | 15.7 | 11.8 | 5.9  | 19.8 | 26.0 | 30.5 | 25.4 | 17.3 | 26.3 | 43.1 | 64.9 | 57.5 | 40.8 | 59.2 | 59.7 |
|       | Semi-Supervised | 60.2 | 53.5 | 35.6 | 56.6 | 65.3 | 52.9 | 49.0 | 36.6 | 45.6 | 61.3 | 77.9 | 71.6 | 54.6 | 71.4 | 68.2 |
|       | Gain          | 44.5 | 41.7 | 29.7 | 36.8 | 39.3 | 22.4 | 23.6 | 19.3 | 19.3 | 18.2 | 13.0 | 14.1 | 13.8 | 12.2 | 8.5 |
| 100 | Supervised* | 35.1 | 30.6 | 19.5 | 36.3 | 40.3 | 45.1 | 38.3 | 26.4 | 38.2 | 54.8 | 66.2 | 61.7 | 45.2 | 62.5 | 60.6 |
|       | Semi-Supervised | 64.6 | 59.0 | 42.2 | 61.9 | 68.8 | 67.3 | 64.9 | 49.2 | 56.9 | 68.6 | 83.7 | 81.9 | 66.6 | 76.4 | 73.3 |
|       | Gain          | 29.5 | 28.4 | 22.7 | 25.6 | 28.5 | 22.2 | 26.6 | 22.8 | 18.7 | 13.8 | 17.5 | 20.2 | 21.4 | 13.9 | 12.7 |

Table 3: Segmentation MoF comparison with SOTA on 3 benchmark datasets. Our ICC can improve its fully-supervised counterpart. Our semi-supervised results is competitive in MoF with different levels of supervision.

|   | Method | Breakfast | 50salads | GTEA |
|---|--------|-----------|----------|------|
| Full | MSTCN’20 | 67.6 | 83.7 | 78.9 |
|     | SSTDA’20 | 70.2 | 83.2 | 79.8 |
|     | *C2F-TCN’21 | 73.4 | 79.4 | 79.5 |
|     | Ours ICC (100%) | 75.2 | 85.0 | 82.0 |
| Weakly | SSTDA(65%) | 65.8 | 80.7 | 75.7 |
|     | TSS’21 | 64.1 | 75.6 | 66.4 |
|     | Ours ICC (40%) | 71.1 | 78.0 | 78.4 |
|     | Ours ICC (10%) | 68.8 | 68.6 | 73.3 |
|     | Ours ICC (5%) | 65.3 | 61.3 | 68.2 |

7 Conclusions

In our work we show that pre-trained input features that capture semantics and motion of short-trimmed video segments can be used to learn higher-level representations to interpret long video sequences. Our proposed multi-resolution representation formed with outputs from multiple decoder layers, implicitly bring temporal continuity and consequently large improvements in unsupervised contrastive representation learning. Our final semi-supervised learning algorithm ICC can significantly reduce the annotation efforts, with 40$\%$ labelled videos approximately achieving fully-supervised (100$\%$) performance. Furthermore, ICC also improves performance even when used with 100$\%$ labels.
A Appendix

In section B we detail our training hyper-parameters used for unsupervised and semi-supervised setup. We also provide variations in results with change in important hyper-parameters of our algorithm to experimentally validate our choice of hyper-parameters. In section C we provide additional detail of the base architecture C2F-TCN (Singhania, Rahaman, and Yao[2021]) used and validate the choice with respect to other base model like ED-TCN (Lea et al. 2017), MSTCN (Li et al. 2020). In section D we experimentally validate the normalization strategy used for our multi-resolution feature and show derivation of temporal continuity implicitly incorporated in it. In section E we show additional experimental and qualitative visualization results. We show visualization of representation learnt and input I3D feature, and show results with IDT as input features in section E.1. The importance of our unsupervised representation learning step in final results is shown in section E.2. We show quantitative and qualitative improvements in representations learnt and semi-supervised classification results with multiple iteration of ICC in section E.3. Finally we report deviations of our results with different selections of labelled videos in E.4.

B Implementation Details & Hyperparameter Selection

All our experiments are conducted on Nvidia GeForce RTX 2080 Ti GPUs with 10.76 Gb memory. We use the Adam optimizer with Learning Rate (LR), Weight Decay (WD), Epochs (Eps), and Batch Size (BS) used for our unsupervised and semi-supervised setup shown in Table 6. For the contrast step of ICCt for i ≥ 2, we reduce the learning rate to be 0.1 times that of the contrast step learning rate used in the first iteration (i.e. ICC1). We use a higher number of epochs for the semi-supervised fine-tuning step, but as the number of labeled data is minimal, the training time is quite less. For all three datasets, we follow the k-fold cross-validation averaging to report our final results of representation, semi-supervised and fully-supervised results (however, we tune our model hyper-parameters for a hold-out validation set from training dataset). Here k = {4, 5, 4} for Breakfast, 50Salads and GTEA respectively and is same as used in other works (Li et al. 2020, Chen et al. 2020a).

B.1 Sampling strategy, number of samples 2K

We show ablations for the choice of 2K i.e. number of representation samples drawn per video as described in section 4.1 of main paper in Table 4. Thus our value of 2K is determined by experimental validation. In 50salads with 2K = 120 and batch size of 50, we get roughly 0.6 million positive samples per batch, with each positive sample having roughly around 6.5K negative samples.

B.2 Input feature clustering

In section 4.1 of the main paper, unsupervised feature learning requires cluster labels from the input features. We cluster at the mini-batch level with a standard k-means and then compare with Finch (Sarfraz, Sharma, and Stiefelhagen [2019]), an agglomerative clustering, that have shown to be useful in the unsupervised temporal segmentation (Sarfraz et al. 2021). Comparing the two in Table 7, we observe that K-means performs better. We speculate that this is because Finch is designed for per-video clustering. In contrast, our clustering on the mini-batch is on a dataset level, i.e., over multiple video sequences of different complex activities.

For choosing k in the K-means clustering, we choose ≈ 2A (A denotes number of unique actions) number of clusters resulting in K = {100, 40, 30} for Breakfast, 50Salads, and GTEA datasets, respectively. The advantage of using ≈ 2A clusters versus simply A is verified in Table 7. The improvement is greater for datasets with fewer action classes like GTEA and 50salads than the Breakfast action dataset.

C Details And Choice Of Base Architecture

C.1 Details of C2F-TCN

Our base architecture is same as C2F-TCN (Singhania, Rahaman, and Yao[2021]), which takes snippet-level features like IDT or I3D as input and which has convolution block used for encoder-decoder of kernel size 3 with total of 4.07 million trainable parameters. To train the C2F-TCN, we use downsampled input features and a multi-resolution augmentation training strategy as recommended by (Singhania, Rahaman, and Yao[2021]). We briefly discuss down sampling and augmentation used here and also show its effect on our unsupervised feature learning in Table 8.

Downsampling: The pre-trained input feature representations i.e I3D and IDT referenced as V ∈ R^{T x F} and the ground truth y of temporal dimension T is downsampled by w to obtain the input feature vector V_{in} ∈ R^{T_{in} x F} and ground truth y_{in} of temporal dimension T_{in}, where T_{in} = \frac{T}{w}. This is done by max-pooling the features using a temporal window of size w and assigning the corresponding label which is most frequent in the given window. Specifically, if the input feature and ground truth label at time i.e \ V_{in}^{w} [i] and y_{in}^{w} [i] for some temporal window w > 0 is, then the

Table 4: Ablation results of number of samples per video required for representation learning.

| %D_L | Method     | F1@[10, 25, 50] | Edit | MoF |
|-------|------------|-----------------|------|-----|
| 100%  | Full-Supervised | 68.0 | 63.9 | 52.6 | 52.6 | 64.7 |
| 5%    | Supervised  | 32.4 | 26.5 | 14.8 | 25.5 | 39.1 |
| 5%    | our ICC     | 39.3 | 34.4 | 21.6 | 32.7 | 46.4 |
| 5%    | Gain        | 63.9 | 79.9 | 6.8  | 7.2  | 7.3  |

Table 5: Our semi-supervised (final ICC) results with EDTCN (Lea et al. 2017) on 50salads with 5% labelled data significantly improves over its supervised counterpart.
We try our entire algorithm for semi-supervised temporal learning with unsupervised representation learning and iterative contrast learning. In Table 7: Unsupervised Representation’s MoF variation with MSTCN (Li et al. 2020) architecture, possibly due to the fact that MSTCN is not designed for representation learning as 3 out of the 4 model blocks consists of refinement stages, where each stage takes class probability vectors as input from the previous stages. Therefore, representation learning and classifier cannot be decoupled, making alternative classifier-representation learning algorithm impossible. Further, MSTCN do not have multiple temporal resolution representation like encoder-decoder architecture which play a significant role in our contrastive learning as discussed earlier.

### C.2 Other baseline models
We try our entire algorithm for semi-supervised temporal segmentation (outlined in section 5, Figure 4 of main paper) with unsupervised representation learning and iterative contrast classify with two other base TCN models: ED-TCN (an encoder-decoder architecture) and MSTCN (wavenet like refinement architecture).

ED-TCN: We show our proposed ICC to be working with ED-TCN (Lea et al. 2017) in Table 5, where ICC improves performance over its supervised counterpart. Due to smaller capacity of ED-TCN compared to C2F-TCN (indicated by the fully supervised performance (top row of Table 5) of ED-TCN 64.7% vs C2F-TCN 79.4% MoF), ICC algorithm improvement with ED-TCN is lower than improvement with C2F-TCN. For contrastive framework, an increased performance with better model capacity has also been shown before in SimCLR (Chen et al. 2020b).

MSTCN: Our proposed algorithm does not work well with MSTCN (Li et al. 2020) architecture, possibly due to the fact that
feature is discussed in Section 4.3 of the main paper. For the ‘nearest’ neighbor upsampling strategy, the multi-resolution feature \( f \) has the property of being similar for nearby frames. Coarser features like \( \{z_1, z_2, z_3\} \) are more similar than fine-grained features at higher decoder layers. This also gives independence to the higher resolution features to have high variability even for nearby frames. Specifically, for two frames \( t, s \in \mathbb{N} \), if \( \lfloor t/2^u \rfloor = \lfloor s/2^u \rfloor \) for some integer \( u > 0 \) then \( \text{sim}(f[t], f[s]) \geq 1 - u/3 \). This follows from the fact that for nearest upsampling, \( \lfloor t/2^u \rfloor = \lfloor s/2^u \rfloor \) for some \( 0 \leq u \leq 5 \), implies that

\[
z_v[t] = z_v[s] \quad \text{for all} \quad 1 \leq v \leq 6 - u. \tag{9}
\]

Table 10: Our learned representation linear evaluation of segmentation’s MoF significantly improves upon input IDT features. * indicates evaluations based on publicly available checkpoints.

Table 8: Impact of using Multi-Resolution Augmentation

| Method          | Breakfast | 50Salads | GTEA          |
|-----------------|-----------|----------|---------------|
|                 | \( F\{10, 25, 50\} \) | \( \text{Edit} \) | \( \text{MoF} \) | \( F\{10, 25, 50\} \) | \( \text{Edit} \) | \( \text{MoF} \) | \( F\{10, 25, 50\} \) | \( \text{Edit} \) | \( \text{MoF} \) |
| No Augment      | 55.6 50.2 36.5 49.4 69.4 | 40.0 34.1 29.0 31.0 62.3 | 70.0 63.4 47.2 65.6 69.0 |
| Augment         | 57.0 51.7 39.1 51.3 70.5 | 40.8 36.2 28.1 32.4 62.5 | 70.8 65.0 48.0 65.7 69.1 |

Table 9: Importance of normalization order for Multi-Resolution Feature

| Representation | Breakfast | 50Salads |
|----------------|-----------|----------|
| IDT + CTE-MLP  | 45.0      | 34.1     |
| IDT            | 18.2      | 36.9     |
| Ours (Input IDT) | 67.9 52.2 |           |
| Gain           | +49.7     | +13.3    |

Table 10: Experiment Result with IDT features: We omitted representation segmentation results when using IDT features as input to C2F-TCN. In Table 10 of the main paper, we show that trends in improvement of our representation compared to input IDT features are similar to the results of Table 1 of the main paper.

E Additional Ablation

E.1 Unsupervised Representation learning

Visualization of representations learnt: In Table 1 of the main paper we show the representations results for 13D features as input to C2F-TCN. In Figure [5] we visualize our learnt representation versus input 13D features with the help of UMAP(used for visualization by reducing data to 2-dimensions) visualization. We show our learnt representation incorporate separability based of actions and therefore have much higher segmentation linear classifier scores that input 13D features (Table 1 of main paper).

Experiment Result with IDT features: We omitted representation segmentation results when using IDT features as inputs to C2F-TCN instead of 13D due to space limitations and include it here in Table [10] IDT features are obtained in unsupervised way with use of PCA and Gaussian Mixture Models [Wang and Schmidt 2013] compared to 13D obtained from pre-trained models. We show that trends in improvement of our representation compared to input IDT features are similar to the results of Table 1 of the main paper.
Figure 5: Change in UMAP scatter plot (McInnes, Healy, and Melville 2018) after our unsupervised representation learning. The plot is of seven videos of the complex activity “fry egg”. Each point in the plot denotes a frame of a video while different colors represent different actions (specified in the legend). Left subplot shows the discriminativeness of input I3D features, while the right one shows representation obtained by our unsupervised learning. In the left figure, each of the connected path-like blobs belong to different videos. Meaning the I3D features of the frames of the same video are well-connected in the feature space and suggest that temporal continuity is the primary factor behind the distinction in the feature space. In contrast (in the right figure), our learned representation separates actions across different videos. There are also some locally-connected components in the right figure which actually belong to the frames of the same video which are of the same action as well. Hence, rather than separating frames primarily based on temporal continuity (like the I3D feature) our learned feature primarily separates based on action, and then locally on the basis of temporal continuity (same video).

Table 11: “ICC-wo-unsupervised” (removing the initial unsupervised representation learning from ICC) on 50salads with 5% $D_L$. The ICC results are from fourth iteration i.e. (ICC₄).

| Method               | F1@10 | F1@25 | F1@50 | Edit | MoF |
|----------------------|-------|-------|-------|------|-----|
| Supervised           | 30.5  | 25.4  | 17.3  | 26.3 | 43.1|
| ICC-wo-unsupervised  | 42.6  | 37.5  | 25.3  | 35.2 | 53.4|
| ICC-with-unsupervised| 52.9  | 49.0  | 36.6  | 45.6 | 61.3|

Table 12: Improvement in representation on 50salads for 5% labelled data with more iterations of ICC. Note: Representation is evaluated with 100% data with simple Linear Classifier as discussed in section 4.4.

|                  | F1@10 | F1@25 | F1@50 | Edit | MoF |
|------------------|-------|-------|-------|------|-----|
| Unsupervised     | 40.8  | 36.2  | 28.1  | 32.4 | 62.5|
| ICC₂             | 51.3  | 46.6  | 36.5  | 44.7 | 61.3|
| ICC₃             | 52.5  | 47.2  | 36.5  | 45.4 | 62.1|
| ICC₄             | 52.6  | 47.7  | 38.1  | 46.7 | 61.3|

Unsupervised Clustering vs Representation Learning:
We also report the linear classification scores for the publicly available checkpoints of unsupervised segmentation CTE-MLP (Kukleva et al. 2019) (which pre-trains representation for predicting the absolute temporal positions of features) in Table 10. Surprisingly, linear classifier accuracy of the representation from there unsupervised work is below the input IDT features baseline for 50Salads. This is likely due to there assumptions made of embedding the absolute temporal positions to the features before clustering, when positions of actions within 50salads is widely different in different videos of the dataset. However, we note, as discussed in related work section 2 of the main paper, unsupervised works like (Kukleva et al. 2019; Li and Todorovic 2021; Sarfraz et al. 2021) is based on development of clustering algorithms, with requirement of higher order viterbi algorithm. Using the same representation with two different clustering algorithm, the segmentation results can vary widely. For example, IDT features of 50salads has MoF of 29.7% with Viterbi+Kmeans and 66.5% with TWFINCH (Sarfraz et al. 2021) as shown in (Sarfraz et al. 2021). So our unsupervised representation learning step is not directly comparable to unsupervised clustering(segmentation) algorithms. They can only evaluate there unsupervised clusters based on Hungarian Matching to ground truth labels (i.e. no classifier is trained, only creates segmentation without labelling and temporal action segmentation requires to jointly segment and classify all actions) and therefore they cannot be compared to fully-semi-weakly supervised works.
We discuss our detailed semi-supervised algorithm in section 5 of our main paper and provide visualization of the algorithm in Figure 4. We summarize it with an Algorithm 1 in supplementary.

## E.2 ICC without unsupervised step.

In Table 11 we show results of our ICC without the initial “unsupervised representation learning” as “ICC-Wo-Unsupervised”. This essentially means that the 2nd row of Table 11 represents the scenario in which from our ICC algorithm we remove the 1st contrast step that is learned with cluster labels. The improvement in scores over supervised setup is quite low compared to the full-ICC with the unsupervised pre-training, shown as “ICC-With-Unsupervised”. This verifies the importance of our unsupervised learning step in ICC.

## E.3 Iterative progression of ICC results

We discuss our detailed semi-supervised algorithm in section 5 of our main paper and provide visualization of the algorithm in Figure 4. We summarize it with an Algorithm 1 in supplementary.

### Improvement after Contrast step

In Table 12 we show the improvement in representation after each contrast step. Due to the usage of better pseudo-labels obtained from the preceding classify step, the following contrast step results in better representations as more iteration is performed. For 5% labelled videos of the 50salads dataset, we can see that there is a clear improvement in F1 and Edit scores as more iterations are performed. Note that the evaluation of the learned representation is same as described in subsection 4.4 of the main text.

### Improvement after Classify step

In Table 2 of main text, we showed the progressive improvement in performance for 5% labelled videos, evaluated after the classify step of each ICC iteration. In Table 13 we show the same progressive improvements for 10% and 100% labelled videos. The evaluation is done after the classify step of each iteration of the algorithm. Our ICC raises overall scores on all datasets, with stronger improvements in F1 and Edit scores.

### Qualitative visualization of segmentation

We show in Figure 6 an example segmentation results from 50salads dataset of how the segmentation results improves (becomes more aligned to GT shown with increase in MoF and F1@50) with more iterations of ICC.

## E.4 Standard deviations in results

We show our standard deviations in results for 50Salads, Breakfast dataset for variations in labelled data used in Table 14. We show the variation in results for ICC1 and ICC4 when we take 5 different random selections of 5%, 10% labelled videos in Breakfast and 50Salads from corresponding training splits. We report the mean and standard deviation for different choices as mean ± std format.

| %DL | Method | F1@{10, 25, 50} | Edit | MoF  | F1@{10, 25, 50} | Edit | MoF  | F1@{10, 25, 50} | Edit | MoF  |
|-----|--------|-----------------|------|------|-----------------|------|------|-----------------|------|------|
| ≈10 | ICC1   | 57.0 51.9 36.3 | 56.3 | 65.7 | 51.1 45.6 34.5 | 42.8 | 65.3 | 82.2 78.9 63.8 | 75.6 | 72.2 |
|     | ICC2   | 60.0 54.5 38.8 | 59.5 | 66.7 | 56.5 51.6 39.2 | 48.9 | 67.1 | 83.4 80.1 64.2 | 75.9 | 72.9 |
|     | ICC3   | 62.3 56.5 40.4 | 60.6 | 67.8 | 60.7 56.9 45.0 | 52.4 | 68.2 | 83.5 80.8 64.5 | 76.3 | 73.1 |
|     | ICC4   | 64.6 59.0 42.2 | 61.9 | 68.8 | 67.3 64.9 49.2 | 56.9 | 68.6 | 83.7 81.9 66.6 | 76.4 | 73.3 |
|     | Gain   | 1.6 1.3 2.3 | 2.6 | 3.1 | 1.6 2.2 3.2 | 4.2 | 3.3 | 1.5 2.0 2.8 | 0.8 | 1.1 |
| 100 | ICC1   | 68.1 63.5 49.4 | 66.5 | 72.2 | 72.2 69.1 59.9 | 62.2 | 79.7 | 89.9 88.1 79.2 | 84.7 | 80.9 |
|     | ICC2   | 71.5 67.6 54.5 | 68.0 | 74.9 | 78.4 75.8 68.5 | 71.1 | 82.9 | 89.9 88.3 75.6 | 85.3 | 80.9 |
|     | ICC3   | 71.9 68.2 54.9 | 68.5 | 75.0 | 81.3 79.3 71.9 | 74.4 | 84.5 | 90.1 88.3 78.3 | 86.8 | 81.0 |
|     | ICC4   | 72.4 68.5 54.9 | 68.6 | 75.2 | 83.8 82.0 74.3 | 76.1 | 85.0 | 91.4 89.1 80.5 | 87.8 | 82.0 |
|     | Gain   | 4.3 5.0 5.5 | 2.1 | 3.0 | 11.6 12.9 14.4 | 13.9 | 5.3 | 1.5 1.0 1.3 | 3.1 | 1.4 |

Table 13: Quantitative evaluation of progressive semi-supervised improvement with more iterations of ICC with ≈ 10% and 100% labelled data.

Figure 6: A qualitative example taken from 50salads, showing progressive improvement in segmentation results with number of iterations of ICC. Some segments becomes more aligned to ground truth (GT) leading improved MoF and F1@50 scores.
Table 14: Mean and standard deviation for 5 different selections of 5% and 10% labelled videos from Breakfast and 50salads. For each metric we report the results in the format mean ± std, i.e. the means and the standard deviation for the 5 runs.

| Dataset     | ICC(Num Videos) | F1@10 | F1@25 | F1@50 | Edit | MoF |
|-------------|-----------------|-------|-------|-------|------|-----|
| Breakfast   |                 |       |       |       |      |     |
| ICC1 (≈ 63 Videos) | 54.5 ± 1.2 | 48.7 ± 1.1 | 33.3 ± 1.1 | 54.6 ± 0.9 | 64.2 ± 1.3 |
| ICC4 (≈ 63 videos) | 60.2 ± 1.5 | 53.5 ± 1.3 | 35.6 ± 0.9 | 56.6 ± 1.2 | 65.3 ± 1.8 |
| ICC1 (≈ 120 Videos) | 57.0 ± 1.9 | 51.9 ± 2.1 | 36.3 ± 1.3 | 56.3 ± 1.2 | 65.7 ± 1.9 |
| ICC4 (≈ 120 Videos) | 64.6 ± 2.1 | 59.0 ± 1.9 | 42.2 ± 2.5 | 61.9 ± 2.2 | 68.8 ± 1.3 |
| 50salads    |                 |       |       |       |      |     |
| ICC1 (3 Videos) | 41.3 ± 1.9 | 37.2 ± 1.5 | 27.8 ± 1.1 | 35.4 ± 1.6 | 57.3 ± 2.3 |
| ICC4 (3 videos) | 52.9 ± 2.2 | 49.0 ± 2.2 | 36.6 ± 2.0 | 45.6 ± 1.4 | 61.3 ± 2.3 |
| ICC1 (5 Videos) | 51.1 ± 2.1 | 45.6 ± 1.3 | 34.5 ± 1.7 | 42.8 ± 1.1 | 65.3 ± 0.8 |
| ICC4 (5 videos) | 67.3 ± 1.8 | 64.9 ± 2.5 | 49.2 ± 1.8 | 56.9 ± 2.1 | 68.6 ± 0.7 |

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