Learning Actor-centered Representations for Action Localization in Streaming Videos using Predictive Learning

Sathyanarayanan N. Aakur
Oklahoma State University
Stillwater, OK 74078
saakurn@okstate.edu

Sudeep Sarkar
University of South Florida
Tampa, FL 33620
sarkar@usf.edu

Abstract

Event perception tasks such as recognizing and localizing actions in streaming videos are essential for tackling visual understanding tasks. Progress has primarily been driven by the use of large-scale, annotated training data in a supervised manner. In this work, we tackle the problem of learning actor-centered representations through the notion of continual hierarchical predictive learning to localize actions in streaming videos without any training annotations. Inspired by cognitive theories of event perception, we propose a novel, self-supervised framework driven by the notion of hierarchical predictive learning to construct actor-centered features by attention-based contextualization. Extensive experiments on three benchmark datasets show that the approach can learn robust representations for localizing actions using only one epoch of training i.e., we train the model continually in streaming fashion - one frame at a time, with a single pass through training videos. We show that the proposed approach outperforms unsupervised and weakly supervised baselines while offering competitive performance to fully supervised approaches. Finally, we show that the proposed model can generalize to out-of-domain data without significant loss in performance without any finetuning for both the recognition and localization tasks.

1. Introduction

Understanding events in video sequences requires understanding beyond recognition, such as localizing the actor, understanding their future behavior from current and past observations, and building robust representations at the event-level and the object level. While many recent works have focused on action recognition [1, 18, 22] and action localization [6, 14, 36], significant progress has primarily been driven by the use of large-scale, annotated training data. There has been exciting progress in learning self-supervised representations in video data [7, 9, 41, 44] and has reduced the need for labeled data for recognition, but there is still a dependency on annotations for localization.

In this work, we tackle the problem of learning actor-centered representations through continual, hierarchical predictive learning to localize actions in streaming videos without labeled data by drawing inspiration from cognitive theories of human perception. We define an actor-centered representation as a compositional representation of the scene that encodes the properties (location, geometry, and relational cues, to name a few) of the dominant actor in the scene that contributes most to the action of interest. For example, in Figure 1, there can be many objects (three players, soccer ball, etc.) in the scene, but only one (the player in the middle) is the dominant actor in action “kicking ball”. Hence, an actor-centered representation would encode the appearance and geometry of the player in the middle and contextualize their features with respect to the other objects in the scene. Such representations allow us
to capture action-specific contextual cues in a generalizable representation and have a basis in physiological and neuro-psychological results in humans and monkeys [5, 28].

Cognitive theories of human event perception [48, 49] suggest that humans build event representations by contextualizing the actor’s features with environment-level (or scene) at both a perceptual level (such as color, texture, and movement) and a conceptual level (such as actor-environment interactions and action goals). The notion of hierarchical predictive learning is used to model the evolution of both the environment and the actor by constructing and predicting actor-centered representations in a streaming fashion. Computationally, we model this process by following a sequence of operations given by observe, predict, compare, attend, contextualize, and localize. Figure 1 illustrates this process, which follows a common working assumption in theories of event perception in humans [47, 48, 49]. The key idea is that predictable features or objects do not attract attention and hence do not contribute to the action of interest. Based on the surprise-attention hypothesis [11, 12], we introduce the idea of contextualized, hierarchical prediction that enables the algorithm to select objects of interest and maintain context in prediction to localize the action by navigating spurious motion patterns such as camera motion, background clutter, and object deformation, to name a few.

Contributions: The contributions of our approach are three-fold: (i) we introduce the idea of hierarchical predictive learning to learn actor-centered representations to localize actions in streaming videos in a self-supervised manner, (ii) introduce a novel, attention-driven formulation for learning actor-centered features to help maintain context in future feature prediction, and (iii) show that the use of actor-centered feature representations helps learn robust features that can generalize to data from outside the training domain without finetuning for both localization and recognition.

3. Actor-centered Action Localization

Problem Formulation. In our setup, we consider the problem of localizing the dominant action $a_i$ at each time instant $t$ in a streaming video. Each video can contain multiple objects in the scene with one dominant actor perform-
ing a specific action of interest. The key challenge is ignore clutter and identify the object of interest (i.e., the actor) without any supervision while building robust representations that capture the motion and relational dynamics of the scene. Figure 2 illustrates the proposed action localization framework using actor-centered representations. We jointly model both the evolution of the action and the actor in a single, unified framework with only a single epoch of training.

3.1. Extracting Perceptual Features

First, we extract a global, scene-level representation of the given visual sequence. This representation includes both perceptual features as well as identifying regions of likely interest, such as objects. While our approach is general enough to handle different object proposal approaches, we use a pre-trained convolutional neural network to extract the scene-level representation ($f^S_t$) and use a Single-Shot Object Detector (SSD) [24] layer to generate region-proposals ($B^S_t$), where objects are likely to exist. Following prior work in [3], we make the SSD to be class-agnostic by considering all bounding boxes returned (at an “objectness” threshold of 0.01) regardless of the predicted class and their corresponding confidence scores. This allows us to remove any biases towards certain types of actors, such as human actors, and help handle any visual variations (such as pose and occlusion) that can cause missed detections.

3.2. Event-centric Perception

The second step in the proposed model is to construct a feature representation of the current scene (at time $t$) influenced by the observed event’s spatial-temporal dynamics. While CNN features provide an efficient spatial representation, it does not consider the contextual knowledge provided by temporal transitions and spatial interactions among the scene’s entities. This representation is analogous to the use of working memory in cognitive theories of event perception in humans [49, 48]. This process requires modeling a stable event representation $h^E_t$ and an attention mechanism $\alpha^S_t$ that uses this global representation to jointly perceive and anticipate the spatial and temporal dynamics of the event. Formally, we define the event-centric perception model as a prediction function that maximizes the probability $P(\hat{f}^S_{t+1}|W_p, \alpha^S_t, h^E_t, f^S_t)$, where $\hat{f}^S_{t+1}$ is the anticipated features at time $t+1$ conditioned on an internal event representation $h^E_t$, a temporally-weighted, spatial attention function $\alpha^S_t$ and the current observed features $f^S_t$. $W_p$ is the set of learnable parameters in this module.

There are two steps in constructing the event-centric perceptual features - (i) learning an efficient global, event-level representation and (ii) using the learned event representation to drive the perception in a recurrent, cyclical manner. First, we first create the event-centric scene representation by weighting the CNN feature $f^S_t$ of the frame at time $t$ by an attention vector ($\alpha^S_t$), influenced by the spatial temporal dynamics of the current event. Hence, the event-centric representation is given by $f^E_t = \alpha^S_t \circ f^S_t$, where $\alpha^S_t = f_a(f^S_t, h^E_{t-1})$ and $f_a(\cdot)$ is a learned attention function [4]. Note that we do not concatenate this attention-weighted representation with the CNN feature as is the case with traditional uses of attention. Second, we use a hierarchical stack of Long Short Term Memory (LSTM) networks [10] to construct the internal event representation. We take a continual predictive learning approach, inspired by [2, 3], to learn an efficient global representation of the event that captures the relevant spatial-temporal patterns to provide context for event-based perception. The hierarchical LSTM stack is used as a spatial-temporal decoder network, which takes in as input a sequence of event-centric image features and propagates its prediction up the stack. The output of the top-most LSTM is taken as the anticipated features ($\hat{f}^S_{t+1}$) at the next time step. Hence, the hierarchical LSTM stack acts as a generative model that learns and uses a stable event representation to anticipate the scene’s spatial and temporal evolution. Formally, the whole process is represented as

\[
\hat{f}^t_{t+1}, h^f_t = \text{LSTM}(\hat{f}^{t-1}_{t+1}, W_f, h^f_{t-1})
\]

\[
f^0_{t+1}, h^0_t = \text{LSTM}(f^E_t, W_0, h^0_{t-1})
\]

where $\hat{f}^{t-1}_{t+1}$ refers to the predicted features at the $t$th LSTM in the stack and $W_f$ refers to the weights associated with the LSTM at the $t$th layer; Equation 2 shows the initialization of the prediction framework for the bottom-most 0th-layer LSTM. Note that $\hat{f}^f_{t+1}$ for the top most LSTM network is taken as the prediction for time $t + 1$ and the corresponding hidden state is taken as the event representation such that $h^f_t = h^f_{t-1}$ and $\hat{f}^S_{t+1} = \hat{f}^S_{t+1}$. Note that the memory is not shared within the stack as done in [3] and hence allows each level of the stack to model the spatial-temporal dynamics at different granularity, with each the prediction of the LSTM at the $t$th level influenced by the lower-level LSTMs.

**Learning** The whole stack is trained in a predictive learning approach with the training objective given by

\[
\mathcal{L}_{\text{event}} = \|f^S_{t+1} - \hat{f}^S_t\|_2 \circ \hat{f}^S_{t+1} - \|\hat{f}^S_{t+1}\|_2
\]

where the first term represents the weighted difference between the features at consecutive time steps $t$ and $t + 1$ and the resulting value $\mathcal{L}_{\text{event}}$ represents a weighted $L - 2$ norm of the predicted and expected value that penalizes incorrect predictions at spatial locations with maximal change at the feature level. Hence, $\mathcal{L}_{\text{event}}$ is the prediction-based drive, a measure of the effectiveness of the learned event representation at a coarse spatial quantization.

3.3. Contextualization: Actor-centered Features

At the core of the proposed approach is the notion of building actor-centered representations. We consider a fea-
ture representation of a scene to be actor-centered if the resulting representation can (i) reject clutter in the scene, (ii) reduce the impact of background or spurious motion patterns, and (iii) contextualize the actor’s (object of interest) motion dynamics with the rest of the scene or environment. This representation is analogous to a posterior-weighted spatial representation that highlights areas of interest while suppressing spatially irrelevant features. In our framework, the posterior is obtained by the dot-product multiplication of the prior (the prediction-based error from Equation 3) and the observation ($f^E_t$). The contextualized representation is obtained by computing the dot-product attention [25] between the posterior-weighted representation and the actual representation and is defined as

$$f^O_t = GAP(\text{softmax}(f^S_t \odot F^S_t) \odot F^S_t)$$

where $GAP$ refers to the Global Average Pooling function [23] and $F^S_t$ is a contextualized feature representation conditioned by the posterior probability obtained by the spatial-temporal prediction loss $L_{\text{Event}}$. We compute this function as $F^S_t = \text{softmax}(L_{\text{Event}}) \odot f^S_t$, which intuitively provides a representation that rejects clutter by scaling down the spatial regions that do not contribute to the prediction uncertainty. These areas typically involve background scenes or actors whose actions are more predictable and less likely to be of interest.

Note that we use the Global Average Pooling function to construct the final, frame-level object-contextualized representation. The idea is to generate one global representation that captures the attention-scaled local features at each spatial location. This operation forces the network to learn correspondences between the raw spatial features and the prediction-based posterior. Thus, it helps preserve the scene’s spatial-temporal structure by summing out any trivial motion-based changes, making it more robust to spurious motion patterns in the input, such as those induced by background noise and small camera motion, which are common in real-life, every-day videos. Empirically, we find that this formulation results in a more robust video-level representation that can generalize across domains (Section 4.4) for both the localization task and as well as the recognition task.

### 3.4. Hierarchical Predictive Learning

We use the notion of continual, hierarchical predictive learning to train the model end-to-end in a self-supervised manner. The goal of this approach is to model the dynamics of the observed event at different levels of granularity, moving beyond just scene-level dynamics [3] or temporal dynamics [2]. In addition to the event-level predictive stack (Section 3.2), we also model the evolution of the actor with respect to the scene. However, we do not predict the actor-centered representations independent of the event-level predictions. Rather, we model the object dynamics conditioned upon the event representation by constructing a global representation given by $f^E_t = GAP(\alpha_t^S \odot f^S_t)$, where $f^S_t$ refers to the anticipated spatial features (from the previous prediction step) and $\alpha_t^S$ refers to the spatial attention constructed (conditioned on the current observation) at time $t$. This formulation of the global representation forces the model to learn spatially relevant features that are important across time steps and hence helps ensure that the event representation is robust by acting as temporal smoothing.

Given this global representation, we learn two LSTM-based prediction models that use this representation to anticipate the actors’ dynamics in terms of contextualized features and geometry. One LSTM anticipates the changes in the actor’s geometry rather than directly predicting the BB location, which allows the predictor to focus on the evolution of geometry. Hence, the goal of these two LSTMs is to minimize the actor-centered prediction errors defined as

$$L_{\text{object}} = ||f^O_t - f^O_t||_2 + D_{\text{obj}}(b_t, b_t) + D_{\text{bb}}(b_t, b_t)$$

where $D_{\text{obj}}(b_t, b_t)$ is the distance between the predicted bounding box and the actual observed bounding centers; $D_{\text{bb}}(b_t, b_t) = (\sqrt{w} - \sqrt{w})^2 + (\sqrt{h} - \sqrt{h})^2$, where $h$ and $w$ are the predicted height and widths of the bounding box, respectively. The predicted bounding box is given by $b_t = b_{t-1} + \hat{b}_t$, where $b_{t+1}$ is the offset of the bounding box predicted by the actor-centered LSTM predictor described above. Hence, the overall objective function is given by

$$L_{\text{total}} = \lambda_1 \frac{1}{n_f} \sum_{i=1}^{w_f} \sum_{j=1}^{h_f} L_{\text{event}} + \lambda_2 L_{\text{object}}$$

where $\lambda_1$ and $\lambda_2$ are modulating factors to balance the trade-off between predicting the event-level and object-level prediction errors. Note that both loss functions directly penalize the event-level representation ($b^E_t$), the spatial attention ($\alpha^S_t$) and the contextualization module ($F^S_t$). Hence, the loss function acts as a form of multi-task learning objective, acting as implicit regularization to prevent overfitting since the model’s parameters are updated continuously per frame. The resulting spatial-temporal loss $L_{\text{event}}$ can then considered to be reflective of the predictability of both the actor and scene. Hence, spatial locations with a higher error indicate the location of the actor [3, 11].

### 3.5. Attention-based Action Localization

The final step in the proposed approach is using attention to localize the actor (the object of interest) in the given video. Inspired by [3], we use create an attention-like representation using the prediction-based error $L_{\text{event}}$ to identify areas of interest. The input to the localization process consists of (i) initial regions of interests generated based on spatial features $B^S_f$ (from Section 3.1), (ii) the spatial-temporal prediction error $L_{\text{event}}$ (from Section 3.2), (iii)
number of attention “grids” to consider \( K \), and (iv) the total number of bounding box predictions per frame \( t \). We first construct an attention-like representation by running the spatial-temporal prediction error through a softmax function to produce an attention map of shape \( c_x \times c_y \) where \( c_x \) and \( c_y \) are spatial dimensions of the observed feature maps, with each point corresponding to a “grid” in the frame (following notation from YOLO [29]). The softmax operation magnifies areas of high errors while suppressing areas of low prediction errors.

Following prior work [3], we consider areas of high prediction error to be regions of interest. However, we allow the attention map to be split between multiple objects and consider the top \( K \) grids (sorted based on prediction error) to select bounding box localization. Following the notation from YOLO-based object detection models [29], we define a binary function \( \mathbb{1}(\cdot) \) that returns True if a bounding box proposal’s center falls within the “grid” \( e_{i,j} \) and False otherwise. This allows us to select objects that are most likely to contribute to the grid’s prediction error. Note that this is different from [3], where each bounding box is assigned an energy term based on distance from a predicted error position and the magnitude of the prediction error, which does not allow them to attend to multiple objects in the same frame. The framework could be expanded to localize simultaneous actions in the same video by using separate actor-centered representations per attention grid. We leave that to future work, since it is beyond the scope of this paper.

### 3.6. Implementation Details

In our experiments, we use a VGG-16 network [33], pre-trained on ImageNet [31], as the backbone network for training a Single Shot Multibox Detector (SSD) [24] to extract frame-level representations and generate action localization jointly. The SSD network is trained on MS-COCO for object detection and then fine-tuned on VideoLSTM [22], Action Tubes [8], ALSTM [32], Tube CNN [13], VideoLSTM [22], and Action Tubes [8] to produce a spatial-temporal prediction error through a softmax function. We use the SSD as a class-agnostic region proposal network with input re-sizes to \( 512 \times 512 \). We use the output of the max-pooling layer after the fifth convolutional layer as \( f^S \).

We use the SSD as a class-agnostic region proposal network by taking the bounding box proposals without using any predicted classes or associated probabilities. The number of layers \( f \) in the hierarchical prediction network (in Section 3.2) as 3 and set the dimensions of the hidden state at each layer to 512. We use the vanilla LSTM as proposed in [10], with each spatial “grid” fed in sequentially for prediction. We set the number of attention grids \( K = 5 \) and the number of localization per frame \( N = 10 \) (Section 3.5). We train with the adaptive learning mechanism proposed in [2], with the initial learning rate set to be \( 1 \times 10^{-10} \) and scaling factors \( \Delta_t \) and \( \Delta^r \) as \( 1 \times 10^{-1} \) and \( 1 \times 10^{-2} \), respectively. The network was trained for 1 epoch. We use the same hyperparameters for all experiments.

### 4. Experimental Evaluation

#### 4.1. Data

We use three standard benchmark datasets (UCF Sports [30], JHMDB [15], and THUMOS’13 [17]) to evaluate the proposed approach for action localization. UCF Sports [30] contains 10 classes characterizing sports-based actions such as weight-lifting and diving. We use the official splits containing 103 videos for training and 47 videos for testing, as defined in [20] for evaluation. JHMDB [15] has 21 action classes from 928 trimmed videos, each annotated with human-joints and bounding box for every frame. It offers several significant challenges for self-supervised action localization, such as camera motion that causes significant occlusions and background objects that act as distractions. We report all results as the average across all three splits. THUMOS’13 [17] (or the UCF-101-24 dataset) is a subset of the UCF-101 [37] dataset, consisting of 24

| Approach               | Supervision | UCF Sports | JHMDB | THUMOS’13 |
|------------------------|-------------|------------|-------|-----------|
|                        |             | \( \sigma = 0.2 \) | \( \sigma = 0.5 \) | \( \sigma = 0.2 \) | \( \sigma = 0.5 \) |
| Tube CNN [13]          | ✓           | 0.47       | -     | 0.77      | 0.47     |
| Action Tubelets [14]   | ✓           | 0.53       | 0.27  | -         | 0.48     |
| Action Tubes [8]       | ✓           | 0.56       | 0.49  | 0.55      | 0.45     |
| ALSTM [32]             | ✗           | -          | -     | 0.06      | -        |
| VideoLSTM [22]         | ✗           | -          | -     | 0.37      | -        |
| Actor Supervision [6]  | ✗           | -          | 0.48  | 0.36      | 0.46     |
| Soomro et al [36]      | ✗           | 0.46*      | 0.30* | 0.43*     | 0.22*    |
| PredLearn [3] \((k=k_{gt})\) | ✗       | 0.55       | 0.32  | 0.30      | 0.10     |
| Ours \((k=k_{opt})\)   | ✗           | 0.70       | 0.59  | 0.43      | 0.15     |
| PredLearn [3] \((k=k_{opt})\) | ✗       | 0.55       | 0.32  | 0.61      | 0.19     |
| Ours \((k=k_{opt})\)   | ✗           | 0.76       | 0.64  | 0.68      | 0.26     |

Table 1. Comparison with state-of-the-art approaches on three common benchmark datasets - UCF Sports, JHMDB and THUMOS’13. We report the video-level mAP at different overlap thresholds. * refers to the use of class-specific object proposals.
classes and 3,207 videos. It is one of the most challenging action localization datasets with complex motion, background clutter and high intra-class variability. Following prior works [22, 36], we report results on the first split.

### 4.2. Metrics and Baselines

Due to the self-supervised nature of learning representations, we use \( k\text{-means} \) clustering to obtain class labels. The frame-level features are max-pooled to obtain video-level features. Following prior work [3, 16, 46], we use the Hungarian method to map from predicted clusters to the ground-truth labels. We set the number of clusters to the number of classes in the ground-truth for comparison with state-of-the-art. For the action localization task, we report the mean average precision (mAP) metric at different overlap thresholds for a fair comparison with prior works [22, 36].

**Baselines.** We compare against several fully supervised baselines such as tube convolution networks [13], motion-based action tublets [14] and action tubes [8] and weakly supervised such as ALSTM [32], VideoLSTM [22] and Actor Supervision [6]. We also evaluate our approach against unsupervised action localization approaches such as Soomro et al. [36] and the closely related predictive learning approach [3], which we term as PredLearn. We compare against PredLearn when the number of clusters is set to the ground-truth clusters (\( k = k_{\text{gt}} \)) and optimal (\( k = k_{\text{opt}} \)).

### 4.3. Quantitative Analysis

We first present the quantitative results of the proposed approach in Table 1, where we compare against different baseline approaches. We report the mean average precision (mAP) scores over the most commonly reported overlap thresholds of 0.2 and 0.5. The approaches are ordered by the amount of supervision required for training. The models at the top require supervision in terms of spatial annotations such as bounding boxes and video-level labels to localize and classify the action. The models in the middle are weakly supervised and hence only require video-level labels for training. The approaches at the bottom require no training annotations. It can be seen that our approach outperforms all baselines, including fully supervised models, on the UCF Sports dataset, even at higher thresholds. It is interesting to note that we significantly outperform PredLearn, which is the most similar to our approach, by a significant margin.

On datasets with significantly higher complexity, such as JHMDB and THUMOS’13, we see consistent improvements over the other unsupervised models such as PredLearn and Soomro et al.’s action discovery approach, who use bounding box proposals from class-specific proposals and hence are restricted to objects (such as humans) that are present in the pre-trained object detection models. On the other hand, we use class-agnostic proposals and are not restricted to any object class. Also, it is interesting to note that the use of hierarchical predictive learning and actor-centered feature representations help overcome the challenges posed by occlusions and clutter, as indicated by the significant gains over PredLearn at higher thresholds on JHMDB and THUMOS’13.

**Quality of localizations.** We also independently assess the quality of the localization returned by the approach by computing the recall of the bounding boxes returned. We summarize the results in Table 2. Again, it can be seen that the approaches with full supervision (top half) have a higher recall at a more stringent overlap threshold of \( \sigma = 0.5 \) while the recall and mAP drop with decreasing levels of supervision. However, it is interesting to note that our approach has a higher recall than both weakly supervised and unsupervised baselines at higher overlap thresholds while also significantly improving (7% absolute mAP) upon prior unsupervised localization approaches.

### 4.4. Generalization to Novel Domains

In addition to evaluating the proposed approach in traditional settings, we also assess its ability to generalize to novel domains. To be specific, we check its generalization capability by training on one dataset and testing its performance on a different dataset without finetuning. This is different from traditional settings of self-supervised representation learning where the model is generally finetuned with labels on the target data.

**Action Localization** We begin by evaluating the approach on the generalization task by training the model on the training data from one of the three common benchmarks

| Approach            | Average Recall | mAP@0.2 |
|---------------------|----------------|---------|
| Action Tubelets [14]| 0.43 (0.50)    | 0.38 (0.63+) |
| Learning to Track [45]| -              | 0.47    |
| ALSTM [32]          | 0.46 (0.20)    | 0.56    |
| VideoLSTM [22]      | 0.71 (0.32)    | 0.37    |
| Actor Supervision [6]| 0.89 (0.04)    | 0.46    |
| PredLearn [3]       | 0.84 (0.58)    | 0.33 (0.59+) |
| Ours                | 0.86 (0.24)    | 0.56 (0.63+) |

Table 2. Quality of localization on THUMOS’13. We report average recall at various overlap thresholds and the mAP at 0.2 overlap. * refers to evaluation with optimal clusters \( k = k_{\text{opt}} \).

| Test Data → | UCF Sports | JHMDB | THUMOS’13 |
|-------------|------------|-------|-----------|
| Train Data ↓| \( \sigma = 0.5 \) | \( \sigma = 0.2 \) | \( \sigma = 0.2 \) |
| UCF Sports  | 0.59 (0.32) | 0.39 (0.19) | 0.38 (0.20) |
| JHMDB       | 0.48 (0.23) | 0.43 (0.30) | 0.35 (0.26) |
| THUMOS’13   | 0.50 (0.27) | 0.40 (0.24) | 0.38 (0.31) |

Table 3. Generalization capability of the approach when evaluated on out-of-domain test samples without finetuning. Numbers in parenthesis refer to PredLearn [3].
(UCF Sports, JHMDB - Split 1, and THUMOS’13) and evaluating on the others. We also report the closely related PredLearn approach’s performance, which does not use hierarchical prediction and actor-centered representations. Table 3 summarizes the results. It can be seen that the proposed approach generalizes well across datasets, regardless of the size of the training data. It is to be noted that the model is not finetuned on any data in the target domain yet performs as well as weakly supervised models such as VideoLSTM (0.37 mAP@0.2 on THUMOS’13).

**Action Recognition** We also evaluate the proposed approach’s representation learning ability for the action recognition task. We use the first split of UCF-101 [37] and HMDB-51 [19] datasets as the evaluation data following prior work in Motion Statistics [41]. We summarize the results in Table 4 and compare against early self-supervised approaches. We evaluate the performance under two conditions, (i) when the number of clusters is set to the ground truth number of classes (\(k_{gt}\)) and (ii) allow for over-segmentation by setting \(k = 2k_{gt}\). Note that we do not finetune on any data and use the model trained on THUMOS’13 to obtain video-level features for clustering. It can be seen that we can learn robust representations that allow the model to cluster the videos in more complex datasets with significantly more classes to a reasonable level while obtaining competitive performance with models finetuned on the domains when allowed to over-segment. We see that the clusters’ homogeneity score was 79% for UCF-101 and 63% when allowed to over-segment i.e. setting \(k = 2k_{gt}\). This indicates that although the number of clusters is higher than the ground-truth, the videos in the same cluster were mostly from the same label.

### 4.5. Ablation Experiments

In addition to quantitative analysis, we systematically evaluate the different components of the proposed approach. First, we examine the effect of the changing the number of attention “grids” used in the attention-based action localization (Section 3.5). We evaluate multiple values of “grids” (\(K_{attn}\) for brevity) and summarize the results in Figure 3(a). It can be seen that as the \(K_{attn}\) increases, the localization performance also increases and allows the model to keep track of the object of interest even if there are other objects with less predictable motion.

Similarly, we evaluate the effect of the different terms in the actor-centered prediction loss (\(L_{obj}\) from Equation 5). As can be seen from Figure 4(b), the use of both geometry prediction and contextualized feature prediction help improve the performance significantly, with the use of contextualized prediction providing a greater jump in performance. In Figure 4(c), we present the effect of using event-centric perceptual features (Section 3.2) on the framework with and without hierarchical prediction. It can be that the use of both improves the performance, especially at higher thresholds, indicating that the use of hierarchical prediction with event-centric features helps attend to areas of interest and reject clutter.

We also evaluated the localization performance of the approach when trained with out-of-domain data. Figure 4(d) shows that the real performance drop is at higher overlap thresholds when testing on data outside of the training domain. However, the use of more attention grids \(K_{attn}\) helps alleviate this issue to a certain extent and even outperforms models trained in the same domain.

### 5. Qualitative Analysis

We qualitatively analyze our approach and visualize some interesting instances in Figure 4. We show two specific groups of examples - (i) a comparison with
### 6. Conclusion and Future Work

In this work, we introduce a hierarchical predictive learning framework that continuously predicts and learns from errors at different granularities. The resulting spatial-temporal error was used to localize the action. The model leverages a novel actor-centered representation to learn robust features that mitigate the effect of camera motion, background clutter, and object deformations. The approach obtains state-of-the-art results on unsupervised action localization with only one epoch of training while generalizing to novel domains without finetuning. We aim to expand the framework to tackle self-supervised localization of simultaneous actions in cluttered scenes with complex interactions.

---

**Figure 4.** Top: **Qualitative Examples** of the advantages of using hierarchical predictive learning with actor-centered representations to handle camera motion and background motion to maintain context in localization. **Below:** Unsuccessful localizations. **Visualization Legend:** Red BB: Groundtruth, Green BB: Our prediction, Blue BB: PredLearn prediction, Blue Square: Error-based Attention Location

PredLearn [3] to highlight the importance of using actor-centered features and hierarchical prediction, and (ii) some failure modes of the approach. In rows 1 and 4, it can be seen that although there are other objects in the scene whose motion is unpredictable, the use of multiple attention grids and actor-centered prediction helps the model to maintain focus on the actor. Row 3 shows that the model can overcome the challenges posed by camera motion and object deformation to maintain context in prediction, whereas PredLearn (without hierarchical prediction) is influenced by the camera motion and loses track of the object. In row 2, we visualize an instance where the model loses focus due to background motion. Still, due to the actor-centered predictions, it regains attention to localize the object of interest. We also visualize some of the failure modes of the proposed model in the final row in Figure 4. In particular, we would like to highlight two areas that lead to failure. First, consider the sequence on the left. The model’s attention is initially on the wrong player in the scene and continues to attend to areas of the same player, which we attribute to the actor-centered prediction. Although the object is well localized, it is not the labeled object of interest, to which the model does not have access. The second failure mode, highlighted in the sequence on the right, is bounding box selection. Although the attention is on the object for most frames, the use of class-agnostic proposals returns poorer bounding box fit.
References

[1] Sathyanarayanan Aakur, Fillipe DM de Souza, and Sudeep Sarkar. Going deeper with semantics: Exploiting semantic contextualization for interpretation of human activity in videos. In IEEE Winter Conference on Applications of Computer Vision (WACV). IEEE, 2019.

[2] Sathyanarayanan N. Aakur and Sudeep Sarkar. A perceptional guidance framework for self-supervised event segmentation. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR), June 2019.

[3] Sathyanarayanan N Aakur and Sudeep Sarkar. Action localization through continual predictive learning. arXiv preprint arXiv:2003.12185, 2020.

[4] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. arXiv preprint arXiv:1409.0473, 2014.

[5] Jon Driver, Gordon C Baylis, Susan J Goodrich, and Robert D Rafal. Axis-based neglect of visual shapes. Neuropsychologia, 32(11):1353–1356, 1994.

[6] Victor Escorcia, Cuong D Dao, Mihir Jain, Bernard Ghanem, and Cees Snoek. Guess where? actor-supervision for spatiotemporal action localization. Computer Vision and Image Understanding, 192:102886, 2020.

[7] Chuang Gan, Boqing Gong, Kun Liu, Hao Su, and Jianxiong Xiao. DeepLab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence, 39(7):1343–1356, 2017.

[8] Georgia Gkioxari and Jitendra Malik. Finding action tubes. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 5589–5597, 2018.

[9] Min Lin, Qiang Chen, and Shuicheng Yan. Network in network. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2559–2568. IEEE, 2014.

[10] Tian Lan, Yang Wang, and Greg Mori. Discriminative figure-centric models for joint action localization and recognition. In 2011 International Conference on Computer Vision, pages 2556–2563. IEEE, 2011.

[11] Hsin-Ying Lee, Jia-Bin Huang, Maneesh Singh, and Ming-Hsuan Yang. Unsupervised representation learning by sorting sequences. In Proceedings of the IEEE International Conference on Computer Vision, pages 667–676, 2017.

[12] Zhenyang Li, Kirill Gavrilyuk, Efstratios Gavves, Mihir Jain, and Cees GM Snoek. Video2slm convolves, attends and flows for action recognition. Computer Vision and Image Understanding, 166:41–50, 2018.

[13] Min Lin, Qiang Chen, and Shui-Cheng Yan. Network in network. arXiv preprint arXiv:1312.4400, 2013.

[14] Wei Liu, Dragomir Anguelov, Dumitru Erhan, Christian Szegedy, Scott Reed, Cheng-Yang Fu, and Alexander C Berg. Ssd: Single shot multibox detector. In European Conference on Computer Vision, pages 21–37. Springer, 2016.

[15] Minh-Thang Luong, Hieu Pham, and Christopher D Manning. Effective approaches to attention-based neural machine translation. arXiv preprint arXiv:1508.04025, 2015.

[16] Hossein Mobahi, Ronan Collobert, and Jason Weston. Deep learning from temporal coherence in video. In Proceedings of the 26th Annual International Conference on Machine Learning, pages 737–744, 2009.

[17] Carl R Olson and Sonya N Gettner. Object-centered direction selectivity in the macaque supplementary eye field. Science, 269(5226):985–988, 1995.

[18] Joseph Redmon and Ali Farhadi. Yolo9000: better, faster, stronger. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 7263–7271, 2017.

[19] Mikel Rodriguez, Javed Ahmed, and Mubarak Shah. Action mach a spatio-temporal maximum average correlation.
height filter for action recognition. In 2008 IEEE Conference on Computer Vision and Pattern Recognition, pages 1–8. IEEE, 2008.

[31] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. International Journal of Computer Vision (IJCV), 115(3):211–252, 2015.

[32] Shikhar Sharma, Ryan Kiros, and Ruslan Salakhutdinov. Action recognition using visual attention. In Neural Information Processing Systems: Time Series Workshop, 2015.

[33] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556, 2014.

[34] Khurram Soomro and Mubarak Shah. Unsupervised action discovery and localization in videos. In Proceedings of the IEEE International Conference on Computer Vision, pages 696–705, 2017.

[35] Khurram Soomro, Haroon Idrees, and Mubarak Shah. Unsupervised action discovery and localization in videos. In Proceedings of the IEEE International Conference on Computer Vision, pages 1–8. IEEE, 2008.

[36] Khurram Soomro and Mubarak Shah. Unsupervised action discovery and localization in videos. In Proceedings of the IEEE International Conference on Computer Vision, pages 696–705, 2017.

[37] Khurram Soomro, Amir Roshan Zamir, and Mubarak Shah. Ucf101: A dataset of 101 human actions classes from videos in the wild. arXiv preprint arXiv:1212.0402, 2012.

[38] Yicong Tian, Rahul Sukthankar, and Mubarak Shah. Spatiotemporal deformable part models for action detection. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 2642–2649, 2013.

[39] Du Tran, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. Learning spatiotemporal features with 3d convolutional networks. In Proceedings of the IEEE International Conference on Computer Vision, pages 4489–4497, 2015.

[40] Du Tran and Junsong Yuan. Max-margin structured output regression for spatio-temporal action localization. In Advances in neural information processing systems, pages 350–358, 2012.

[41] Jiangliu Wang, Jianbo Jiao, Linchao Bao, Shengfeng He, Yunhui Liu, and Wei Liu. Self-supervised spatio-temporal representation learning for videos by predicting motion and appearance statistics. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 4006–4015, 2019.

[42] Limin Wang, Yu Qiao, and Xiaou Tang. Video action detection with relational dynamic-poselets. In European Conference on Computer Vision, pages 565–580. Springer, 2014.

[43] Xiaolong Wang and Abhinav Gupta. Unsupervised learning of visual representations using videos. In Proceedings of the IEEE International Conference on Computer Vision, pages 2794–2802, 2015.

[44] Yi Wang, David M Krum, Enyton M Coelho, and Doug A Bowman. Contextualized videos: Combining videos with environment models to support situational understanding. IEEE Transactions on Visualization and Computer Graphics, 13(6):1568–1575, 2007.

[45] Philippe Weinzaepfel, Zaid Harchaoui, and Cordelia Schmid. Learning to track for spatio-temporal action localization. In Proceedings of the IEEE international conference on computer vision, pages 3164–3172, 2015.

[46] Junyuan Xie, Ross Girshick, and Ali Farhadi. Unsupervised deep embedding for clustering analysis. In International Conference on Machine Learning (ICML), pages 478–487, 2016.

[47] Jeffrey M Zacks and Khena M Swallow. Event segmentation. Current Directions in Psychological Science, 16(2):80–84, 2007.

[48] Jeffrey M Zacks and Barbara Tversky. Event structure in perception and conception. Psychological bulletin, 127(1):3, 2001.

[49] Jeffrey M Zacks, Barbara Tversky, and Gowri Iyer. Perceiving, remembering, and communicating structure in events. Journal of Experimental Psychology: General, 130(1):29, 2001.