Weakly Supervised Action Selection Learning in Video

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Abstract

Localizing actions in video is a core task in computer vision. The weakly supervised temporal localization problem investigates whether this task can be adequately solved with only video-level labels, significantly reducing the amount of expensive and error-prone annotation that is required. A common approach is to train a frame-level classifier where frames with the highest class probability are selected to make a video-level prediction. Frame-level activations are then used for localization. However, the absence of frame-level annotations cause the classifier to impart class bias on every frame. To address this, we propose the Action Selection Learning (ASL) approach to capture the general concept of action, a property we refer to as “actionness”. Under ASL, the model is trained with a novel class-agnostic task to predict which frames will be selected by the classifier. Empirically, we show that ASL outperforms leading baselines on two popular benchmarks THUMOS-14 and ActivityNet-1.2, with 10.3% and 5.7% relative improvement respectively. We further analyze the properties of ASL and demonstrate the importance of actionness. Full code for this work is available here: https://github.com/layer6ai-labs/ASL.

1. Introduction

Temporal action localization is a fundamental task in computer vision with important applications in video understanding and modelling. The weakly supervised localization problem investigates whether this task can be adequately solved with only video-level labels instead of frame-level annotations. This significantly reduces the expensive and error-prone labelling required in the fully supervised setting [39, 29], but considerably increases the difficulty of the problem. A standard approach is to apply multiple instance learning to learn a classifier over instances, where an instance is typically a frame or a short segment [23, 26, 14]. The classifier is trained using the top-
k aggregation over the instance class activation sequence to generate video probabilities. Localization is then done by leveraging the class activation sequence to generate start and end predictions. However, in many cases, the instances that are selected in the top-k contain useful information for prediction but not the actual action. Furthermore, with top-k selection the classification loss encourages the classifier to ignore action instances that are difficult to classify. Both of these problems can significantly hamper localization accuracy and stem from the general inability of the classifier to capture the intrinsic property of action in instances. This property is known as “actionness” in the existing literature [7, 21].

Ignoring actionness can lead to two major types of error: context error and actionness error. Context error occurs when the classifier activates on instances that do not contain actions but contain context indicative of the overall video class [19, 14]. Figure 1 (a) shows an example of context error. Here, cricket players are inspecting a cricket pitch. The instance clearly indicates that the video is about cricket and the classifier predicts “Cricket Shot” with high confidence. However, no shot happens in this particular instance and including it in the localization for “Cricket Shot” would lead to an error. Actionness error occurs when the classifier fails to activate on instances that contain actions. This generally occurs in difficult instances that have significant occlusion or uncommon settings. An example of this is shown in Figure 1 (b). The action is “Cricket Bowling”, but the classifier

(a) Context error  (b) Actionness error

Figure 1: (a) Context error for the “Cricket Shot” action due to the presence of all cricket artifacts but absence of action. (b) Actionness error for the “Cricket Bowling” action due to the atypical scene despite the presence of action.
fails to activate as the scene is indoors and differs from the usual cricket setting.

Leading recent work [25, 14, 24] in this area propose an attention model to filter out background and then train a classifier on the filtered instances to predict class probabilities. This has the drawback of making it more challenging for the classifier to learn as important context is potentially removed as background.

Our motivation is to design a learning framework that can use the context information for class prediction and at the same time learn to identify action instances for localization. We have seen from the supervised setting that leading object detection [9, 27, 4] and temporal localization [17, 18, 16] methods leverage class-agnostic proposal networks to generate highly accurate predictions. This demonstrates that a general objectness/actionness property can be successfully learned across a diverse set of classes. To this end, we propose a new approach called Action Selection Learning (ASL) where the class-agnostic actionness model learns to predict which frames will be selected in the top-k sets by the classifier. During inference, we combine predictions from the actionness model with class activation sequence and show considerable improvement in localization accuracy. Specifically, ASL achieves new state-of-the-art on two popular benchmarks THUMOS-14 and ActivityNet-1.2, where we improve over leading baselines by 10.3% and 5.7% in mAP respectively. We further analyze the performance of our model and demonstrate the advantages of the actionness approach.

2. Related Work

Weakly Supervised Temporal Action Localization A prominent direction in the weakly supervised setting is to leverage the class activation sequence to improve localization. UntrimmedNet [32] focuses on improving the instance selection step using class activations. Hide-and-seek [30] applies instance dropout to reduce classifier’s dependence on specific instances. W-TALC [26] incorporates a co-activity similarity loss to capture inter-class and inter-video relationships. 3C-Net [23] adopts a center loss to reduce inter-class variations while applying additional action-count information for supervision. Focusing on class activations can be susceptible to context error, and a parallel line of research explores how to identify context instances. STPN [24] extends UntrimmedNet by introducing a class-agnostic attention model with sparsity constraints. BM [24] uses self-attention to separate action and context instances. CMCS [19] assumes a stationary prior on context and leverages it to model context instances. BaSANet [14] explicitly models a separate context class that is used to filter instances during inference. DGAM [28] trains a variational autoencoder to model the class-agnostic instance distribution conditioned on attention to separate context from actions. More recently, TSCN [37] and EM-MIL [22] propose two-stream architectures. TSCN separates the RGB and Flow modules and learns from pseudo labels generated by combining the predictions of the two streams. EM-MIL introduces a key instance and a classification module trained alternately to maintain the multi instance learning assumption.

Actionness Learning Our approach is motivated by related work in the supervised setting where a common design choice is to learn a class-agnostic module to generate proposals that are then labelled by the classifier [17, 18, 16]. Earlier work defines actionness as a likelihood of a generic but deliberate action that is separate from context [7], and applies it to detect human activity in both image [7] and video [34] settings. A related concept of “interestingness” has been proposed to identify actions at the pixel level [31]. Work in action recognition shows that generic attributes exist across action classes and can be leveraged for recognition [21]. Similar concept has been demonstrated to be successful for tracking applications [15]. Finally, in object detection, leading approaches heavily leverage class-agnostic proposal networks to first identify regions of high “objectness” [9, 27, 4].

In this work, we demonstrate that the analogous “actionness” property in videos can be effectively learned with only video-level labels.

3. Approach

We treat a video as a set of $T$ instances $\{x_1, ..., x_T\}$, dropping video index to reduce notation clutter. An instance can be a frame or a fixed-interval segment, represented by a feature vector $x_t \in \mathbb{R}^d$. In the weakly supervised temporal localization task, each instance $x_t$ either contains an action from one of $C$ classes or is the background, however, this is unknown to us. Instead, we are given video-level classes $Y \subseteq \{1, ..., C\}$ which is the union of all instance classes in the video. The weakly supervised temporal localization task then asks whether video-level class information can be used to localize actions across instances. In this section, we first outline the classification framework in Section 3.1, and then describe our approach in Section 3.2.

3.1. Base Classifier

We define a video classifier to predict target video-level classes as:

$$s_{c,t} = F_{c,t}(x_1, ..., x_T)$$

where $F$ is a neural network applied to the entire video, and $F_{c,t}(\cdot)$ denotes its output at class $c$ and instance $x_t$. Taken over all $T$ instances we refer to $F_{c,t}(\cdot)$ as the class activation sequence (CAS). Multiple instance learning [5] is commonly used to train the classifier, where top-k pooling is
applied over CAS for each class to aggregate the highest activated instances and make video-level predictions. We denote the set of top-\(k\) instances for each class as \(T^c\):

\[
T^c = \arg \max_{T \subseteq \{1, ..., T\}} \sum_{t \in T} h_{c,t}
\]

where \(k\) is a hyper-parameter and \(h_{c,t}\) is the instance selection probability that is used to select the top instances. In prior work, the selection probability is straightforwardly set to the CAS with \(h_{c,t} = s_{c,t}\). However, we make a deliberate distinction here which allows incorporating actionness as we demonstrate in the following section. Aggregation, such as mean pooling, is applied over the selected instances in \(T^c\) to make video-level class prediction:

\[
p_c = \text{softmax} \left( \frac{1}{|T^c|} \sum_{t \in T^c} s_{c,t} \right)
\]

Finally, this model is optimized with the multiple instance learning objective:

\[
L_{\text{CLS}} = -\frac{1}{|Y|} \sum_{c \in Y} \log p_c
\]

### 3.2. Action Selection Learning in Video

The classifier introduced in the previous section optimizes the classification objective which encourages only instances that strongly support the target video classes to get selected in the top-\(k\) set. This can lead to the inclusion of instances that provide strong context support but do not contain the action (actionness error), and also the exclusion of instances that contain the action but are difficult to predict (context error). Both of these problems do not affect video classification accuracy, but can significantly hurt localization. We address this by developing a novel action selection learning (ASL) approach to capture the class-agnostic actionness property of each instance. The main idea behind ASL is that the top-\(k\) set \(T^c\) used for prediction is likely capturing both context and action instances. However, context information is highly class-specific whereas actions share similar characteristics across classes. Consequently, by training a separate class-agnostic model to predict whether an instance will be in the top-\(k\) set for any class, we can effectively capture instances that contain actions and filter out context. We begin by defining a neural network actionness model \(G\):

\[
a_t = \sigma \left( G_t(x_1, ..., x_T) \right)
\]

where \(\sigma\) is the sigmoid activation function, and \(G_t(\cdot)\) denotes the output of \(G\) for instance \(x_t\). Here, \(a_t\) can be interpreted as the probability that \(x_t\) contains any action.

For an instance to contain a specific action, it should simultaneously contain evidence of the corresponding class and evidence of actionness. As we discussed, class evidence alone is not sufficient and can lead to context and actionness errors. To account for both properties, we expand the instance selection function:

\[
h_{c,t} = h(a_t, s_{c,t})
\]

This selection function combines beliefs from both models and can be implemented in multiple ways. In this work we fuse the scores with a convex combination \(h(a_t, s_{c,t}) = \beta a_t + (1 - \beta)s_{c,t}\) and leave other possible architectures for future work. After \(h_{c,t}\) is computed, we proceed as before and select top-\(k\) instances with the highest \(h_{c,t}\) values to get \(T^c\).

To train the actionness model \(G\), we design a novel task to predict whether a given instance \(x_t\) will be in the top-\(k\) set for any ground truth class. Since context is highly class dependent, we hypothesize that \(G\) can only perform well on this task by learning to capture action characteristics that are ubiquitous across classes. This hypothesis is further motivated by the fact that many leading supervised localization methods first generate class-agnostic proposals and then predict classes for them [17, 18, 16]. High accuracy of these models indicates that the proposal network is able to learn the general actionness property independent of the class, and we aim to do the same here. We first partition instances into positive and negative sets:

\[
T_{\text{pos}} = \bigcup_{c \in Y} T^c
\]

\[
T_{\text{neg}} = \{1, ..., T \} \setminus T_{\text{pos}}
\]

where positive set \(T_{\text{pos}}\) contains the union of all instances that appear in the top-\(k\) for the ground truth classes \(Y\), and negative set \(T_{\text{neg}}\) has all other instances. We then train \(G\) to predict whether each instance is in the positive or negative set. In our model the classifier and actionness networks are tied by the instance selection function. Empirically, we observe that during training as classification accuracy improves better instances get selected into positive and negative sets. This improves the actionness model which translates to better top-\(k\) instance selection for the classifier, leading to further improvement in classification accuracy. The two models are thus complementary to each other, and we show that both classification and localization accuracy improve when the actionness network is added.

Since our target positive and negative sets contain both context and action instances, the binary inclusion labels can be noisy. This is particularly the case early in training when classification accuracy is poor and top selected instances are not accurate. Traditional cross entropy classification loss assigns a large penalty when prediction de-
For each class we select top-3 instances with the highest action selection probabilities and aggregated together to generate class prediction \( p_c \) for the video. Finally, the union of top-3 instances across ground-truth classes \( Y \) is used to generate target sets \( T_{pos} \) and \( T_{neg} \) for the actionness model. (b) Toy example illustrates how target sets \( T_{pos} \) and \( T_{neg} \) are computed. The video has \( T = 7 \) instances, \( C = 4 \) classes and \( k = 3 \). For each class we select top-3 instances with the highest action selection probabilities \( h(a_t, s_{c,t}) \) indicated by yellow cells. Taking union of selected instances across ground truth classes \( c \in Y \) we get \( T_{pos} \) shown in blue. All other instances form \( T_{neg} \) shown in red.

The proposed ASL architecture is summarized in Figure 2(a). Figure 2(b) also shows a toy example that illustrates how target sets \( T_{pos} \) and \( T_{neg} \) are computed. The video has \( T = 7 \) instances and \( C = 4 \) classes, two of which are in the ground truth \( Y = \{3, 4\} \). Moreover, \( k = 3 \) so for each class top-3 instances with the highest instances selection probabilities \( h(a_t, s_{c,t}) \) are selected, indicated by yellow cells. Union of instances selected for the ground truth classes form \( T_{pos} = \{x_1, x_2, x_3, x_4\} \) shown in red, and all other instances form \( T_{neg} = \{x_5, x_6, x_7\} \) shown in blue. To successfully predict instances in each list, the actionness model must find commonalities between all instances in \( T_{pos} \) and distinguish them from \( T_{neg} \). As we demonstrate in the experimental section this commonality is the presence of actionness which significantly aids the localization task.

After training, we use the instance selection probabilities \( h_{c,t} \) to localize actions in test videos. Given a test video with \( T' \) instances, we run it through our model to get the corresponding instance selection probability sequence \( h_{c,1}^{...}, h_{c,T'} \). We then follow recent work [23, 14, 28] and apply multiple thresholds \( 0 < \alpha < 1 \). All instances where selection probability is above the threshold \( h_{c,t} > \alpha \) are considered selected, and we take all consecutive sequences as proposal candidates. Repeating this process for each threshold, we obtain a set of proposals for each class. We then apply non-maximal suppression to eliminate overlapping and similar proposals and generate the final localization predictions.

4. Experiments

We conduct extensive experiments on two popular weakly supervised temporal localization datasets containing untrimmed videos: THUMOS-14 [11] and ActivityNet-1.2 [3]. THUMOS-14 contains 200 training videos with 20 action classes and 212 test videos. ActivityNet-1.2 contains 4,819 training and 2,383 test videos with 100 action classes.
Both datasets have videos that vary significantly in length from a few seconds to over 25 minutes. This makes the problem challenging since the model has to perform well on both long and short action sequences. For all experiments, we only use video-level class labels during training. To make the comparison fair, we follow the same experimental setup used in literature [26, 23, 14, 28], including data splits, evaluation metrics and input features. For all experiments, we report average precision (AP) at the different intersection over union (IoU) thresholds between predicted and ground truth localizations. For brevity, we show selected thresholds in the results table for both datasets. The mAP is computed with IoU thresholds between 0.1 to 0.9 with increments of 0.1 on THUMOS-14 and between 0.5 to 0.95 with increments of 0.05 on ActivityNet-1.2 to stay consistent with previous work. Full results on all thresholds used for computing mAP are found in the supplementary material.

**Implementation Details** We generate instance input features $x_t$ following the same pipeline as recent leading approaches [23, 14, 28]. The 13D network [6] pre-trained on the Kinetics dataset [12] is applied on each sub-sequence of 16 consecutive frames with RGB and TVL1 flow [33] inputs to extract 2048-dimensional feature representation by spatiotemporally pooling the Mixed5c layer. Linear interpolation across time is then applied for both datasets. To make the comparison fair we adopt the same base classifier $F$ as in [14] with 512 hidden units and ReLU activations. Similarly, the actionness network $G$ is fully connected with 512 hidden units. Both networks are applied across time to every instance and operate similarly to convolutional features.

**Ablation**

| Approach | AP@IoU | mAP |
|----------|--------|-----|
| CMCS [19] | 57.4 41.2 23.1 7.0 - - | - |
| MAAN [36] | 59.8 41.1 20.3 6.9 0.2 | 24.9 |
| 3C-Net [23] | 56.8 40.9 24.6 7.7 - - | - |
| BaSNet [14] | 58.2 44.6 27.0 10.4 0.5 | 27.9 |
| BM [25] | 60.4 46.6 26.8 9.0 0.4 | 28.6 |
| DGAM [28] | 60.0 46.8 28.8 11.4 0.4 | 29.2 |
| ACL [10] | - 46.9 30.1 10.4 - - | - |
| TSCN [37] | 63.4 47.8 28.7 10.2 0.7 | 22.9 |
| EM-MIL [22] | 59.1 45.5 30.5 16.4 - - | - |
| **ASL (ours)** | **67.0 51.8 31.1 11.4 0.7** | **32.2** |

| Approach | AP@IoU | mAP |
|----------|--------|-----|
| ASL-$s_{c,t}$ | 56.9 40.5 19.7 6.0 0.4 | 24.0 |
| ASL-$a_t$ | 55.9 40.3 20.6 6.8 0.4 | 30.4 |
| ASL-BCE | 66.4 50.5 30.5 10.9 0.7 | 31.6 |

**Results** Table 1 summarizes temporal localization results on the THUMOS-14 dataset. Our approach improves over the prior art by a significant margin on all IoU thresholds except 0.7, with a 10.3% relative gain in mAP over the best baseline. A similar pattern can be observed from the ActivityNet-1.2 results summarized in Table 2. We can see that ASL improves over every baseline on all IoU thresholds except 0.5, with a 5.7% relative gain in mAP. These results indicate that the proposed action selection learning framework is highly effective for the weakly supervised temporal localization task. Figure 3 further breaks down THUMOS-14 performance by class. The top four classes with the largest relative improvement are highlighted in blue. The most improved classes have more than 100% relative gain. We believe this is due to the wide range of context settings present in the dataset for these classes, making class-agnostic action learning more effective for separating context.

**Ablation** To demonstrate the importance of actionness, we conduct ablation study on the THUMOS-14 dataset shown at the bottom of Table 1. Here, ASL-$s_{c,t}$ uses class probability $h_{c,t} = s_{c,t}$ and ASL-$a_t$ uses actionness probability $a_t$, respectively to localize, and ASL-BCE trains the actionness network $G$ with the binary cross entropy loss.

**Table 1:** THUMOS-14 results. mAP is the mean of AP@IoU scores across thresholds \( \{0.1, 0.2, ..., 0.9\} \). Ablation results are shown at the bottom where ASL-$s_{c,t}$ and ASL-$a_t$ use class probability $s_{c,t}$ and actionness probability $a_t$ respectively to localize, and ASL-BCE trains the actionness network $G$ with the binary cross entropy loss.

**Table 2:** ActivityNet-1.2 results. mAP is the mean of AP@IoU scores across thresholds \( \{0.5, 0.55, ..., 0.95\} \).
The classification for ASL-$a_t$ is done at the video level by taking the class with the highest probability and assigning it to every localization. Finally, ASL-BCE trains the actionness network $G$ with the binary cross entropy loss instead of the generalized $\mathcal{L}_{\text{ASL}}$ loss in Equation 9. We see that incorporating actionness in the full ASL model relatively outperforms the classification-only ASL-$s_{c,t}$ approach by over 36% in mAP. Moreover, ASL-$a_t$ has very strong performance and is competitive with prior state-of-the-art results even though $a_t$ on its own has no explicit class information. This demonstrates that the actionness network $G$ is able to successfully capture the general class-agnostic concept of action through our top-$k$ instance prediction task. Once captured, this property can be effectively used to identify regions within each video where the action occurs independently of the class. We note here that attention models commonly used in prior work, have not been shown to be capable of localizing actions on their own. The full ASL model further improves performance of ASL-$a_t$ by 6% indicating that classifier and actionness networks capture complementary information. Finally, using binary cross entropy instead of the noise tolerant $\mathcal{L}_{\text{ASL}}$ loss hurts performance. $\mathcal{L}_{\text{ASL}}$ becomes equivalent to binary cross entropy in the limit as $q \to 0$ [38]. In all our experiments we found that much higher values of $q$ such as 0.7 produced better performance on both datasets, indicating that cross entropy is indeed not adequate here due to the high degree of noise in the target labels particularly at the beginning of training.

**Actionness Learning** The main idea behind ASL is that actionness can be captured by predicting top-$k$ membership for each instance. In this section, we analyze this learning task in detail. Figure 4 shows various properties of the $T_{\text{pos}}$ set throughout training. In Figure 4(a) we plot the fraction of instances in $T_{\text{pos}}$ that contain ground truth action from any target class. For comparison, we also plot this fraction for ASL-$s_{c,t}$ and ASL-$a_t$ where top-$k$ instances are chosen according to class $s_{c,t}$ and actionness $a_t$ probabilities respectively. We observe that without the actionness model, ASL-$s_{c,t}$ hovers around 63% whereas for ASL it steadily increases to over 72%. Furthermore, ASL-$a_t$ reaches a much higher fraction of over 70% compared to ASL-$s_{c,t}$, capturing a significantly larger portion of instances with action. This again indicates that the actionness network is better at identifying action instances than the classifier.

Figure 4(b) shows the validation accuracy of the actionness model $G$ in predicting which instances are in the $T_{\text{pos}}$ set. Despite the fact that $T_{\text{pos}}$ is a moving target that can change with each iteration, the prediction accuracy remains stable and gradually improves throughout learning reaching over 84%. The model is thus able to reach an equilibrium between the two networks and no divergence is observed. Furthermore, Figure 4(c) shows the intersection over union
(IoU) between the $\mathcal{T}_{pos}$ sets from consecutive epochs during training. A higher IoU indicates a larger overlap between consecutive $\mathcal{T}_{pos}$ sets which in turn makes targets for $G$ more stable and easier to learn. We observe that the initial IoU starts around 0.5 and rapidly approaches 1 as training progresses. Furthermore, the variance in IoU across training videos decreases throughout training so $\mathcal{T}_{pos}$ sets stabilize after the first few epochs. These results indicate that the top-$k$ selection remains consistent for the majority of training epochs, and $G$ is able to successfully learn these targets; we observe this pattern in all our experiments.

Figure 5a breaks down the predictions made by ASL by error type. We use all test instances and show the total number of true positives (TP), false positives (FP), false negatives (FN) and true negatives (TN) with different proportions of action instances. We compare ASL with the classifier-only actionness model. Alternating between $F$ and $G$ is joint ASL training, $F$ then $G$ is sequential training of $F$ followed by $G$, $F:n G:m$ is an alternating schedule where $F$ is updated for $n$ epochs followed by $G$ for $m$ epochs.

Throughout the training, we simultaneously update both $F$ and $G$. We discussed that this results in moving targets for $G$ where instances in $\mathcal{T}_{pos}$ change as the classifier is updated. Alternative training strategies are explored in Figure 5c. We experiment with first training $F$ to convergence and then $G$ ($F$ then $G$), and alternating between training $F$ and $G$. We denote these alternating schedules by $F:n G:m$ to indicate training $F$ for $n$ epochs followed by training $G$ for $m$ epochs and repeating. We observe that training $F$ then $G$ results in the lowest performance, since the model cannot adjust the classifier to work better with the actionness model. Alternating between $F$ and $G$ updates improves performance but still lags behind joint training. This corroborates our intuition that the classifier and actionness models complement each other in ASL and should be trained together.

We further show DETAD [1] analysis on THUMOS-14 dataset in Figure 7. Here, the top row shows false positive analysis (context error) and false negative analysis (action-
5. Conclusion

We propose the Action Selection Learning (ASL) approach for weakly supervised video localization. ASL incorporates a class-agnostic actionness network that learns a general concept of action independent of the class. We train the actionness network with a novel prediction task by classifying which instances will be selected in the top-\(k\) set by the classifier. Once trained, this network is highly effective on its own and can accurately localize actions with minimal class information from the classifier. Empirically, ASL demonstrates superior accuracy, outperforming leading recent benchmarks by a significant margin. Future work includes further investigation into actionness and its generalization to other related video domains.
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