Tragedy Plus Time: Capturing Unintended Human Activities from Weakly-labeled Videos

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Abstract

In videos that contain actions performed unintentionally, agents do not achieve their desired goals. In such videos, it is challenging for computer vision systems to understand high-level concepts such as goal-directed behavior, an ability present in humans from a very early age. Inculcating this ability in artificially intelligent agents would make them better social learners by allowing them to evaluate human action under a teleological lens. To validate this ability of deep learning models to perform this task, we curate the W-Oops dataset, built upon the Oops dataset [11]. W-Oops consists of 2,100 unintentional human action videos, with 44 goal-directed and 30 unintentional video-level activity labels collected through human annotations. Due to the expensive segment annotation procedure, we propose a weakly supervised algorithm for localizing the goal-directed as well as unintentional temporal regions in the video leveraging solely video-level labels. In particular, we employ an attention mechanism based strategy that predicts the temporal regions which contribute the most to a classification task. Meanwhile, our designed overlap regularization allows the model to focus on distinct portions of the video for inferring the goal-directed and unintentional activity, while guaranteeing their temporal ordering. Extensive quantitative experiments verify the validity of our localization method. We further conduct a video captioning experiment which demonstrates that the proposed localization module does indeed assist teleological action understanding. Project website can be found at: https://asu-apg.github.io/TragedyPlusTime.

1. Introduction

Traditional video action recognition [4, 10, 20, 27, 49, 57, 63] focuses on predicting only atomic actions present on the surface appearance of a video. On the other hand, teleological understanding of actions entails understanding the underlying goal of actions and why it was performed. These goals can be easily inferred from intentional actions as they are directly defined by their outcome. However, many actions do end up in unintended results where the goal of the action is partially or never achieved. As shown in Fig. 1, an agent tries to hit the ball with a bat, but ends up landing on his face, hence not being able to achieve his goal of hitting the ball. State-of-the-art action recognition models are all trained with vewing the whole scene as “faceplant” without paying attention to the goal-directed behavior which was to “hit the ball”.

Teleological action understanding provides the invaluable ability to explain and justify an action, as well as learn from mistakes in the case the goal was not achieved [8]. For fine-grained understanding of unintentional actions, it is important to know the goal of the action, why it was not fulfilled, and when (in time) did the action start transitioning away from its goal. These abilities are present in humans from a very early age [2, 7, 18, 44, 60]. However, this is a challenging task for deep learning models since it requires the model to understand high level concepts such as goal-directed behavior from unintentional actions which would not be possible without penetrating deeper than the surface appearance of the action [2]. There are few previous works which have taken initial steps towards teleological action.
understanding. [11] builds a dataset rich in unintentional human actions, along with single point transition times manually labeled by human annotators which separate the intentional and unintentional regions of the video. They also train models on classification and localization tasks. However, it does not contain well defined classes for the goal-directed action or why this goal gets disrupted. [47] focuses on predicting whether an activity was intentional or unintentional, but not the understanding of the underlying goal of an unintentional action. Previous efforts [12, 24, 61] have tried to speculate about all possible effects of actions but do not explore which effects are undesirable.

In order to build a model which is capable of capturing the unintended activity, it is crucial to first build a dataset containing goal-directed actions and why they get disrupted. Additionally, in order to localize their respective regions in time, one may manually label the transition point as in [11] and fully supervise the training. However, these annotations are prohibitively expensive to collect and suffer from human error and bias. Previous works such as [23, 28, 31, 33, 34, 40, 62], which focus on segmenting atomic action scenes from untrimmed videos tackle this problem of expensive manual labelling by training a model in a weakly supervised manner using only video level action labels. Though this task differs from our task (which involves separating the goal-directed action from the region it starts deviating from its goal), it still provides encouragement to solve our task in a weakly supervised manner.

We bring Weakly Augmented Oops (W-Oops), an augmented video dataset, built upon Oops [11], containing high quality video level labels for the goal-directed as well as unintentional action. To the best of our knowledge, we are the first to make a step towards such fine-grained understanding of unintentional actions.

2. We propose an attention mechanism based method that highlights relevant temporal regions of the video important to a classification task when inferring the goal-directed and unintentional action while also ensuring their temporal ordering.

3. Finally, we provide in-depth and comprehensive experimental analysis, which validates the effectiveness of our method compared to competitive weakly supervised action localization methods on W-Oops. Additionally, we demonstrate the teleological ability of our localization module through a video captioning experiment.

2. Related Work

Intent Recognition from Visual Input. There has been an increasing research focus on intent recognition of agents in videos. [58] proposes a hierarchical model to predict the intention, as well as the attention of an agent’s eye gaze from a RGB-D video. [55] focuses on predicting the action, motivation and scenes from an image by using a third order factor graph built using text. [47] proposes an unsupervised algorithm to discriminate between an intentional and unintentional action performed by an agent. [11] too focuses on discriminating between an intentional and unintentional action, as well as predicting the point in an unintentional video when the action deviates from it’s original goal, but does this in a supervised manner. Our work differs from these as we focus on discriminating between the different goal-directed and unintentional action categories in unintentional videos, as well as localizing these action regions in a weakly supervised manner. Action anticipation can also be relevant to predicting an unintentional action or the onset of it. [17, 19, 30, 38, 39] focus on forecasting an event or action based on a small snippet of a video. [51, 56] focus on self supervised learning approaches to predict future action representation using unlabeled videos. [15, 37, 52] focus on predicting a pedestrian’s intent to cross the road using the Joint Attention for Autonomous Driving (JAAD) dataset [36]. Our work differs from this as it not only focuses on the past and not on predicting the future, but is also generalized to more diverse environmental settings.

Weakly Supervised Action localization (WSAL) has been drawing increasing attention due to the expensive manual labelling process involved in a fully supervised setting. Previous efforts involve localizing action regions in an untrimmed video by training a model using only video level action labels [3, 21, 33, 35, 41–43, 46, 50, 59], or sentences [5, 13, 14, 29, 32, 45]. In particular, STPN [33] trains a classification model using sum of features weighted by
their class-agnostic attention weights, which it learns using a sparsity loss on the attention weights. It then performs the localization by using both the classification activation as well as these class-agnostic weights, thresholding them to select action locations. WTALC [34] forces the foreground action features from the same action class to be similar and the background features pertaining to an action class to be dissimilar from its foreground feature, and finally localizes the action by thresholding the classification activation. A2CL-PT [31] uses foreground and background features to form triplets and apply the Angular Triplet Centor Loss [25] to separate the foreground and background features, as well as use an adversarial branch in order to find supplementary activities from non-localized parts of the video. DGAM [40] propose to separate action frames from context frames by modeling the frame representation conditioned on the bottom-up attention. TSCN [62] fuse the attention sequences from the RGB and optical flow stream and use it as pseudo ground truth to supervise the training.

3. Methodology

We intend to identify the goal-directed and unintended human activities, as well as their corresponding moment of occurrence from an unintentional video in a weakly-supervised manner. To be specific, given the video \( V \) and its categorical labels representing the goal-directed activity, \( y_{IA} \), and the unintended activity, \( y_{UA} \), we expect the model to predict the triplets \( \langle s_{IA}, e_{IA}, c_{IA} \rangle \) and \( \langle s_{UA}, e_{UA}, c_{UA} \rangle \), containing the starting point, end point and action class associated with this segment by leveraging only the video-level annotations as weak supervision. We formulate this challenge as a weakly supervised action localization (WSAL) task, and address it using an attention mechanism based approach. We start this section by providing an overview of our model, followed by the details of formulations and our proposed learning objective.

3.1. Task Formulation

To encode the videos, pre-trained 3D neural networks are exploited to extract a set of clip-level representations \( X \). We find that in order to encode the goal-directed and unintentional features from the video, directly using static features is not sufficient. Hence, we encode the clip embedding by an encoder network \( F \), which outputs a joint representation for the goal-directed and unintentional action: \( O = F(X) \), where \( O \in \mathbb{R}^{l \times d} \) denotes the representations in \( d \) dimensions for \( l \) clips. Here, encoder network \( F \) can either be a bidirectional Gated Recurrent Unit or a Transformer Encoder [53]. On this basis, we introduce two bottom-up attention modules, which outputs the temporal attention weights that reflect the temporal importance of clip representations for the goal-directed/unintentional activity respectively. This is achieved by training the model with a classification loss, e.g., multiple instance learning loss. Note that these attention weights are agnostic to the specific action, and are used to identify generic regions of interest. A stack of 1-D Convolution layers with RELU activation between layers, followed by a Sigmoid function is used to obtain the attention weights \( \lambda_{IA}, \lambda_{UA} \in \mathbb{R}^t \) with a scale between 0 and 1.

In order to obtain goal-directed and unintentional features, we compute a dot product between the joint representation \( O \) and each of the bottom-up attention weights \( \lambda_{IA} \) and \( \lambda_{UA} \). These features would represent those parts of the joint representation \( O \), which correspond to the goal-directed and unintentional region respectively. Formally,

\[
O_{IA} = O \cdot \lambda_{IA}, \quad O_{UA} = O \cdot \lambda_{UA}.
\]

We then compute Temporal Class Activation Maps (TCAM) [33], \( O_{IA} \in \mathbb{R}^{l \times N_{IA}}, \quad O_{UA} \in \mathbb{R}^{l \times N_{UA}} \) for the goal-directed as well as unintentional actions, with \( N_{IA} \) and \( N_{UA} \) corresponding to the number of goal-directed and unintentional classes, by employing two weight-sharing linear transformation layer on \( O_{IA} \) and \( O_{UA} \) respectively. These are one dimensional class-specific activations that signify classification scores over time for both the types of actions for each segment (as illustrated in Fig. 2). These class-specific distributions, along with the class-agnostic distributions are used to predict the triplets \( \langle s_{IA}, e_{IA}, c_{IA} \rangle \) and \( \langle s_{UA}, e_{UA}, c_{UA} \rangle \) associated with the goal-directed and unintentional activities respectively.

3.2. Video Encoder

In order to learn a joint representation for inferring the goal-directed and unintentional actions, we use a Bidirectional Gated Recurrent Unit [6] as the video encoder. 3D-CNN architectures like R(2+1)D [49] and I3D [3] capture very short clip level information. However, capturing information which helps discriminate between the goal-directed region and an unintentional region requires longer temporal context which can be modeled by a GRU. Specifically, our GRU consists of a reset gate \( r \) which controls how much importance to give the previous hidden state \( h^{t-1} \) in order to calculate the current hidden state \( h^t \), and an update gate \( u \) which determines how much of the previous hidden state \( h^{t-1} \) should be carried on to the current hidden state \( h^t \). Given the backbone feature \( X \), we compute the hidden state at each time-step \( t \) using the following equations:

\[
\begin{align*}
    z^t &= \sigma(W_z^t X^t + U_z^t h^{t-1}) \quad \text{Update Gate} \\
    r^t &= \sigma(W_r^t X^t + U_r^t h^{t-1}) \quad \text{Reset Gate} \\
    \tilde{h}^t &= \tanh(r^t \cdot U_h^t h^{t-1} + W h^t) \quad \text{New Memory} \\
    h^t &= (1 - z^t) \cdot \tilde{h}^t + z^t \cdot h^{t-1} \quad \text{Hidden State}
\end{align*}
\]

where \( U \) and \( W \) correspond to learnable parameters of this module. In order to capture the forward information flow
\[ \lambda \] signifies the temporal attention weight for a temporal axis for each class to predict the bottom-up attention weights. Finally, we pass the goal-directed and unintentional feature through weight-shared linear layers to extract their respective TCAMs.

\[ \text{Video Encoder} \rightarrow \text{Video Encoder} \]

\[ \text{Goal-Directed Attention Module} \]

\[ \text{Unintentional Attention Module} \]

**Figure 2. Illustration of our overall architecture.** A backbone feature extractor is used to convert raw videos into features, i.e., \( \mathbf{X} \) and is kept frozen throughout the training process. \( \mathbf{X} \) is then passed to a video encoder which can be either a GRU [6] or a Transformer Encoder [53], to extract high level features \( \mathbf{O} \). The two attention modules use \( \mathbf{O} \) to predict the bottom-up attention weights \( \lambda_{\text{IA}} \) and \( \lambda_{\text{UA}} \) for the goal-directed and unintentional action respectively, which are used for the Overlap Regularization. We calculate the goal-directed, i.e., \( \mathbf{O}_{\text{IA}} \) and unintentional feature, i.e., \( \mathbf{O}_{\text{UA}} \) by computing a dot product between \( \mathbf{O} \) and their respective bottom-up attention weights. Finally, we pass the goal-directed and unintentional feature through weight-shared linear layers to extract their respective TCAMs \( \mathbf{C}_{\text{IA}} \) and \( \mathbf{C}_{\text{UA}} \). These TCAMs are used for the MIL Loss.

\[ \bar{h}^{(t)} \] as well as backward information flow \( h^{(t)} \) we use a Bidirectional-GRU and obtain the final representation \( \mathbf{O} \) by concatenating these features from the final hidden layer.

### 3.3. Multiple Instance Learning Loss

Following previous works in weakly supervised action localization [28,31,34], we use the \( k \)-max Multiple Instance Learning (MIL) [64] loss function for classifying the goal-directed and unintentional activities in the video. For each video, we average out the top-\( k \) elements of the TCAMs, i.e., \( \mathbf{C}_{\text{IA}} \) and \( \mathbf{C}_{\text{UA}} \) along the temporal axis for each class to obtain the video-level classification scores \( A_{\text{IA}} \in \mathbb{R}^{N_{\text{IA}}} \) and \( A_{\text{UA}} \in \mathbb{R}^{N_{\text{UA}}} \). Here, \( k \) is set by \( \left\lfloor \frac{L}{s} \right\rfloor \) where \( s \) is a hyper-parameter that regulates the number of clips to consider when making the classification. We then apply a softmax function over class scores, in order to obtain a probability mass function (pmf) over the goal-directed as well as unintentional classes, i.e., \( p_{\text{IA}} \) and \( p_{\text{UA}} \). Let \( y_{\text{IA}} \) and \( y_{\text{UA}} \) be the ground truth label vectors for a video. We then \( l_1 \)-normalize them to obtain ground-truth pmfs \( q_{\text{IA}} \) and \( q_{\text{UA}} \). Finally we conduct cross entropy over these two.

\[
\begin{align*}
L_{\text{cls}}^{\text{IA}} &= \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N_{\text{IA}}} -q_{\text{IA}}^{(j)} \log (p_{\text{IA}}^{(j)}) \\
L_{\text{cls}}^{\text{UA}} &= \frac{1}{N} \sum_{i=1}^{N} \sum_{j=1}^{N_{\text{UA}}} -q_{\text{UA}}^{(j)} \log (p_{\text{UA}}^{(j)}),
\end{align*}
\]

(3)

where \( N \) corresponds to the total number of training videos, and the final loss is the combination of them: \( L_{\text{cls}} = L_{\text{cls}}^{\text{IA}} + L_{\text{cls}}^{\text{UA}} \).

### 3.4. Overlap Regularization

Let \( \lambda_{\text{IA}}^{(t)}, \lambda_{\text{UA}}^{(t)} \in [0,1] \forall t \in [1,T] \) be the bottom-up attention weights for the goal-directed actions and unintentional action respectively, obtained from the respective attention modules. \( \lambda_i \) signifies the temporal attention weight for a clip \( t \). During training, a trivial solution which could be learned by the model is to pay attention to the entire video when inferring the goal-directed and unintentional action, i.e., \( \lambda_{\text{IA}}^{(t)}, \lambda_{\text{UA}}^{(t)} = 1 \forall t \in [1,T] \), though these actions take place at two distinct sections of the video. Simply applying the MIL loss cannot guarantee that such distinctions can be learnt from the data as shown in Section 4.4. We solve this problem by appending an additional regularization term on the overlap of these attention weights:

\[
\begin{align*}
L_{\text{IA}} &= \max_0 \left( 0, \frac{\sum_{r=1}^{N_{\text{UA}}} \lambda_{\text{UA}}^{(r)}}{N_{\text{UA}}} - \frac{l}{p} \right) \\
L_{\text{UA}} &= \max_0 \left( 0, \frac{\sum_{r=1}^{N_{\text{IA}}} \lambda_{\text{IA}}^{(r)}}{N_{\text{IA}}} - \frac{l}{p} \right) \\
L_{\text{overlap}} &= L_{\text{IA}} + L_{\text{UA}},
\end{align*}
\]

(4)

where \( T_{\text{IA}} \) and \( T_{\text{UA}} \) are the set of temporal indices of the bottom-up goal-directed and unintentional attention.

\[ \text{Unintentional feature} \]

\[ \text{Unintentional TCAM} \]

\[ \text{Unintentional feature} \]

\[ \text{Unintentional TCAM} \]

\[ \text{Unintentional feature} \]

\[ \text{Unintentional TCAM} \]
weights at which they are more than a predefined threshold. \( N_{IA} \) and \( N_{UA} \) are the lengths of the sets of activated temporal indices. \( p \) is a design parameter which controls the amount of allowed overlap between the attention maps. Lower the value of \( p \), lower the penalization of overlaps.

In the goal-directed as well as unintentional regions of the video, the attention weights should ideally be low at the borders of their respective ground truth region and high towards the center of this region. Hence we view \( \lambda_{IA}, \lambda_{UA} \) as Gaussian distributions \( P_{IA} \sim \mathcal{N}(\mu_{IA}, \sigma_{IA}^2) \) and \( P_{UA} \sim \mathcal{N}(\mu_{UA}, \sigma_{UA}^2) \). Every unintentional action begins with an agent performing a goal-directed action in order to achieve it’s goal, which then gets disrupted and transitions into an unintentional action. Using this prior that a goal-directed action transitions into an unintentional action, we need to ensure \( \mu_{IA} < \mu_{UA} \). We approach this by formulating the following regularization:

\[
\begin{align*}
\mu_{IA} &= \frac{\sum_{t=1}^{T} P_{IA}^\lambda \cdot t}{\sum_{t=1}^{T} P_{IA}^\lambda}, \\
\mu_{UA} &= \frac{\sum_{t=1}^{T} P_{UA}^\lambda \cdot t}{\sum_{t=1}^{T} P_{UA}^\lambda}
\end{align*}
\]

\( \mathcal{L}_{order} = \max(0, \frac{\mu_{IA} - \mu_{UA}}{q} + \frac{l}{q}), \)

where \( P_{IA}^\lambda \) and \( P_{UA}^\lambda \) are probability distributions obtained by applying softmax over the temporal axis of \( \lambda_{IA} \) and \( \lambda_{UA} \) respectively. \( q \) is a design parameter that helps control the margin by which \( \mu_{UA} \) has to be greater than \( \mu_{IA} \). Our model is end-to-end trained with the overall loss as follows:

\[
\mathcal{L} = \lambda L_{cls} + (1 - \lambda)(\mathcal{L}_{overlap} + \mathcal{L}_{order}),
\]

where \( \lambda \) is the weighting hyper-parameter that controls the trade-off between MIL loss and overlap regularization.

### 3.5. Classification and Localization

After training our network, we use it to classify goal-directed and unintentional actions as well as localize the regions in which they occur. For a single video, after obtaining the pmf \( P_{IA} \) and \( P_{UA} \) over each of the classes, as mentioned in Section 3.3, we use mean average precision (mAP) to conduct evaluation for the classification task. For localization of the goal-directed and unintentional regions, we consider only categories having classification scores i.e., \( A_{IA} \) and \( A_{UA} \) above 0. For each of these categories, we first scale the respective TCAM outputs to [0,1] using a Sigmoid function and weight these using the bottom-up attention weights. This can be formally expressed by:

\[
\begin{align*}
\psi_{IA}(c_{IA}) &= \lambda_{IA} \cdot \text{Sigmoid}(c_{IA}(c_{IA})) \quad c_{IA} \in [1, N_{IA}], \\
\psi_{UA}(c_{UA}) &= \lambda_{UA} \cdot \text{Sigmoid}(c_{UA}(c_{UA})) \quad c_{UA} \in [1, N_{UA}],
\end{align*}
\]

where \( \psi_{IA}(c_{IA}), \psi_{UA}(c_{UA}) \in \mathbb{R}^3 \) are the weighted TCAMs, for the respective classes \( c_{IA} \) and \( c_{UA} \). We finally threshold \( \psi_{IA}(c_{IA}) \) and \( \psi_{UA}(c_{UA}) \) to obtain the triplets \( \langle s_{IA}, e_{IA}, c_{IA} \rangle \) and \( \langle s_{UA}, e_{UA}, c_{UA} \rangle \).

### 4. Experiments

#### 4.1. Dataset & Implementations

**Data Preparation.** The original Oops Dataset [11] consists of 20,338 videos containing unintentional human actions obtained by collating “fail” videos from different users on YouTube. Amazon Mechanical Turkers are then asked to label the time at which the video starts transitioning from the goal-directed action to the unintentional action, as well as indicate whether a video does not indicate an unintentional action.

In order to create our dataset, which is built upon the labeled portion of the Oops dataset, we follow a similar pre-processing step as in [11] by removing those videos that 1). Do not contain an unintentional action 2). Are More than 30 seconds which are likely to contain multiple scenes, as well as those less than 3 seconds which are not likely to contain one full scene 3). Where the transition time occurs in the initial/ending 1% of the video, since there would not be enough context to understand the goal-directed/unintentional action respectively. Post this process, we were left with a total of about 7,800 labeled videos.

The authors of [11] also provide annotations in the form of natural language descriptions, which were obtained by asking Amazon Mechanical Turkers to watch the video and answer: “what was the goal?” and “what went wrong?”. Since we want to collect a distinct set of goal-directed and unintentional actions, we followed a technique similar to the Epic Kitchens Dataset [9], by extracting the verbs and associated noun using the SpaCy\(^1\) dependency parser and concatenating them to form an action. We replace all compound nouns by it’s second noun: e.g., “ride mountain bike” is replaced with “ride bike” and so on. Due to the diversity of the worker’s vocabulary, we find that the resulting actions are of low quality, with many of them having ambiguous meanings, i.e., “fly bike” as well as redundant meanings. In order to overcome this, we manually go over each of these extracted actions and remove those with ambiguous meanings as well as merge the redundant ones, i.e., “jump over fence” and “jump over chair” into a more general “jump over obstacle” category. We finally carry out a human evaluation, going through all the videos manually and ensuring the correctness of the labels, and correcting them if need be. We also give the evaluator an option to discard the video if the goal of the actor was ambiguous. We build an annotation tool in order to make this process easier (refer to the Appendix for details). Finally, we keep a threshold of 15 for the number of videos per goal-directed and unintentional action class, discarding all classes below this threshold, as

\(1\)https://spacy.io/
Table 1. Performance comparison of our model with competitive weakly supervised action localization (WSAL) models. We adjust the WSAL models by attaching two classification heads to compute two TCAMs (for the goal-directed and unintentional action). We then retrain it on our dataset (W-Oops). We can see that our model significantly outperforms the others.

| Architecture | Feature | Segment | mAP @ IoU |
|--------------|---------|---------|-----------|
|              |         |         | 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 | AVG. |
| STPN [33]    | R(2+1)D | Goal    | 44.9 41.7 33.0 25.7 18.3 10.0 5.0 | 3.7 1.2 | 20.4 |
|              |         | UnInt   | 30.9 26.6 21.8 15.7 9.9 5.2 2.8 | 1.8 1.0 | 0.2 12.5 |
| WTALC [34]   | R(2+1)D | Goal    | 45.1 41.8 36.1 28.9 22.8 15.9 10.4 | 8.1 2.0 | 23.5 |
|              |         | UnInt   | 25.5 21.2 15.3 12.6 7.7 4.3 2.3 | 1.0 0.5 | 10.1 |
| A2CL-PT [31] | R(2+1)D | Goal    | 41.1 38.8 34.3 28.4 23.9 16.6 10.9 | 8.4 2.5 | 22.8 |
|              |         | UnInt   | 30.2 24.2 19.8 14.2 8.6 5.0 1.8 | 0.6 0.1 | 11.6 |
| Ours         | R(2+1)D | Goal    | 45.3 45.1 44.0 41.8 39.1 29.5 21.9 | 13.9 3.5 | 31.6 |
| STPN [33]    | I3D     | Goal    | 44.8 42.8 34.9 27.8 19.9 11.3 | 6.1 4.0 | 21.5 |
|              |         | UnInt   | 36.3 31.3 26.1 19.5 13.0 6.8 | 1.7 0.6 | 15.0 |
| WTALC [34]   | I3D     | Goal    | 38.8 36.4 30.4 26.3 18.6 13.1 | 7.2 4.5 | 19.7 |
|              |         | UnInt   | 22.9 18.4 14.2 11.0 6.8 3.6 | 1.2 0.5 | 0.8 |
| A2CL-PT [31] | I3D     | Goal    | 38.1 36.7 31.8 26.6 22.7 17.6 | 12.5 9.0 | 4.9 |
|              |         | UnInt   | 32.4 26.1 21.6 15.3 9.9 5.2 | 1.6 0.7 | 1.2 |
| Ours         | I3D     | Goal    | 51.5 51.3 49.9 44.9 41.1 32.5 | 24.3 14.4 | 5.0 |
|              |         | UnInt   | 39.4 39.0 36.4 32.2 30.0 26.6 | 17.6 10.2 | 2.8 |

Table 2. Mean average precision of activity classification results using different methods. First row shows the mAP of random chance.

we also extract RGB features by creating chunks of 16 consecutive and non-overlapping frames and using the I3D [4] as well as R(2+1)D [39] pretrained architectures to extract clip-level features from these chunks (details provided in the Appendix). This backbone feature extractor is kept frozen throughout the entire training process. The kernel-size of all the 1-D convolutional layers for the bottom-up attention modules are set to 1. The learning rate and loss weighting function are set to $10^{-3}$ and 0.8 respectively. We set the MIL loss hyper-parameter $s$ to 3. The parameters of the Overlap Regularization, $p$ and $q$, are set to 1000 and 10 respectively. Finally we set the number of layers of our bidirectional GRU to 3. Our network is implemented and trained on a machine with a single Tesla X Pascal GPU for 10,000 iterations using the Adam Optimizer [22] with a batch size of 16.

4.2. Goal-directed/Unintentional Action Localization

Our model should be able to focus on the correct regions of the video in order to infer the goal-directed and unintentional action segments, hence understanding the transition between these two. In order to evaluate our model on the task of localizing goal-directed as well as unintentional segments, we follow the standard evaluation protocol for temporal localization tasks by calculating the mean average precision (mAP) over different intersection over union (IoU) thresholds for both the types of actions. Since there are no quantitative results reported on our dataset, we use competitive models from the traditional weakly supervised action localization task as baselines. Since these models are trained using only one classification head which is used to identify the atomic actions in the video, we repurpose these models by adding an additional classification head (for the goal-directed and unintentional action) and bottom-up attention module (in the case of STPN [33]) or addi-
4.3. Goal-directed/Unintent. Action Classification

Given any video our model is trained to predict the goal-directed action as well as the unintentional action it eventually transitions into. Following previous works [33, 34], we use mean average precision (mAP) to evaluate the classification performance of our model on predicting the goal-directed action as well as unintentional action. We report our results in Tab. 2. It is interesting to note that our method performs the best on the classification task as well. For example, it performs 4.1% higher on the Goal cMAP and 6.3% higher on the Unintentional cMAP than A2CL-PT when using an I3D backbone.

4.4. Ablation Study

We conduct an ablation study to analyze various components of our model. We analyze the significance of the overlap regularization introduced in Section 3.4. We observe very clearly in Tab. 3 that only using $L_{cls}$ is not sufficient to localize the goal-directed and unintentional actions, and our final model performs the best. This implies that all components are necessary in order to achieve the best performance and each one is effective. We further analyze the importance of the hyper-parameters $p$ and $q$ used in the overlap regularization in Fig. 4. We can see that increasing $p$ from 1 to $10^3$ results in a significant increase in the average mAP@IoU. This shows that the localization performance increases by penalizing the overlap of the bottom-up attentions more, but plateaus after the $10^3$ mark. Analysing the $q$ hyper-parameter, we notice that increasing the value of $q$ decreases the performance. Since increasing the value of $q$ results in a lower margin of separation between the expectations of the goal-directed and unintentional bottom-up attention weights, we can conclude that a lower value of $q$, i.e., higher margins of separation helps achieve a better localization performance. However, $q = 1$ signifies the extreme case when the margin is equal to the length of the clips, forcing the goal-directed and unintentional atten-
Figure 5. We form the ground truth caption by concatenating the goal-directed and unintentional caption with a *but*.

Figure 6. Pipeline for the captioning experiment (using our localization module).

| Exp. | R [26] | M [1] | C [54] | S [16] |
|------|--------|-------|--------|--------|
| Without Loc. | 16.7 | 37.7 | 29.8 | 14.1 |
| With Loc.    | 17.0 | 38.0 | 33.9 | 19.8 |

Table 4. Captioning results with or without localization module. R, M, C, S denote ROUGE-L, METEOR, CIDEr and SMURF metrics respectively for video captioning evaluations.

Our method improves semantic performance while maintaining the descriptiveness of terms used in the sentence. These metrics clearly show that the teleological ability of our localization module helps a captioning module output more accurate captions on videos containing unintentional actions, which is achieved by the precise capture of unintentional activity in video. We showcase more qualitative examples in the Appendix.

5. Conclusion

In this paper, we propose W-Oops, an augmented unintentional human activity dataset that consists of both goal-directed and unintentional video-level activity annotations, built upon Oops [11]. We consider a weakly supervised task to infer the respective classes as well as the temporal regions in which they occur using only the video-level activity annotations. We further build a neural network architecture which employs a novel overlap regularization on top of the bottom-up attention weights outputted by our attention module, which helps the model focus on distinct parts of the video while maintaining the temporal ordering of these actions when inferring the temporal regions. We conclude from our experiments that our method significantly outperform previous WSAL baselines on our benchmark. The video captioning experiment further verifies the teleological ability of our localization module, which points a promising future research direction for improving captioning quality through teleological analysis.

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