When Did It Happen? Duration-informed Temporal Localization of Narrated Actions in Vlogs

OANA IGNAT, SANTIAGO CASTRO, YUHANG ZHOU, JIAJUN BAO, DANDAN SHAN, and RADA MIHALCEA, University of Michigan, USA

We consider the task of temporal human action localization in lifestyle vlogs. We introduce a novel dataset consisting of manual annotations of temporal localization for 13,000 narrated actions in 1,200 video clips. We present an extensive analysis of this data, which allows us to better understand how the language and visual modalities interact throughout the videos. We propose a simple yet effective method to localize the narrated actions based on their expected duration. Through several experiments and analyses, we show that our method brings complementary information with respect to previous methods, and leads to improvements over previous work for the task of temporal action localization.

Additional Key Words and Phrases: action temporal localization, action duration, vlogs, natural language processing, video processing, multimodal processing

ACM Reference Format:
Oana Ignat, Santiago Castro, Yuhang Zhou, Jiajun Bao, Dandan Shan, and Rada Mihalcea. 2021. When Did It Happen? Duration-informed Temporal Localization of Narrated Actions in Vlogs. ACM Trans. Multimedia Comput. Commun. Appl. 1, 1, Article 1 (January 2021), 18 pages. https://doi.org/10.1145/3495211

1 INTRODUCTION

Targetting the long-term goal of video understanding, recent years have witnessed significant progress in the task of action localization, starting with the localization of one action at a time in a short clip [58] or in a longer untrimmed video [32], all the way to localizing more complex natural language queries in videos [4, 14–16, 22], and recently to localizing complex natural language queries extracted directly from transcripts in online videos [35, 54, 64].

Lifestyle vlogs represent a great challenge and opportunity for this task, as they depict everyday actions in a complex setting. Unlike traditional action datasets [1, 4, 6, 50] or instructional video datasets [36, 54, 64], vlogs contain a wide variety of actions that are more akin to real-life settings, such as “grab my Kindle,” “do some reading,” or “chill out.”

Moreover, vlogs typically include transcripts with complex natural language expressions, which allow us to find an alternative to the costly process of manual annotations. Given the prevalence of vlogs in online platforms, automatically extracting action names from their transcripts can lead to a large-scale inexpensive action dataset. Previous work [36] relied on this technique to build very large datasets of video-action mappings. However, previous work also found that the video and transcript are often misaligned [24, 35]: in the best case, there is a gap of a few seconds between the time when a person verbally expresses the action and when it is visually illustrated.
This paper addresses the task of temporal action localization in vlogs, and makes three main contributions. First, we introduce a dataset of manual annotations of temporal localization of actions that addresses new challenges compared to other action localization datasets. Second, we present 2Seal – a simple yet effective method that leverages both language and vision to temporally localize actions, while also accounting for the expected duration of the actions. Through extensive evaluations, we show that our proposed method can be used along with existing models to improve their performance on temporal action localization. Finally, we conduct an analysis of the results, and gain insight into the role played by the different components, which further suggests avenues for future work.

2 RELATED WORK

Learning connections between vision and language is crucial to many applications. These applications include visual question answering [3, 30, 60], visual content retrieval based on textual queries [25, 36, 38], image and video captioning [3, 10, 61], video summarization with natural language [41, 43], action detection [7, 17, 32], action temporal localization in videos [11, 14–16, 45] and mapping text descriptions to image or video content [28, 29, 45, 47, 59].

**Action Localization Datasets.** Action detection and localization algorithms evolve with the building of complex datasets. From searching YouTube videos, given a set of predefined actions [1, 7, 21], or filming in people’s homes who act based on a scenario [50], these datasets capture the complexity of daily life activities. However, because of the high annotation cost, these methods are not scalable. Currently, the latest trend in the vision community is to search for pre-defined tasks on WikiHow and collect their corresponding videos from YouTube [36, 54, 64]. This process is more efficient and guarantees that more relevant actions are shown in the videos. Another technique for collecting human actions is to perform implicit data gathering [13]: instead of explicitly searching for a pre-defined task, find routine videos that contain a broad range of daily actions.

In our work, we use the data introduced in [24] which identifies if the actions mentioned in the transcripts are present (visible) in the video. Although we use implicit data gathering as proposed in the past, unlike Fouhey et al. [13], who focus on the visual information (hand and object locations), we focus on routine videos that contain rich audio descriptions of the actions being performed, and we use this transcribed audio to extract actions.

**Action Localization Methods.** Methods that reason over text and visual information do this by first extracting the textual embeddings [9, 31, 42] and visual features [7, 56] and then linearly...
mapping them to the same embedding space [4, 5, 14, 15]. This is usually computed using self and cross attention over the textual and visual features. The visual features can be extracted with a convolutional neural net as in [5, 33, 62] or from object bounding boxes [29]. Recent work [34, 52, 53] builds on this approach by combining the attention modules in a large scale Transformer architecture [57]. Their goal is to learn inter-modality and cross-modality relationships that can be used in downstream tasks that require complex reasoning about natural language grounded in visual data [18, 23, 51].

**Instructional vs. Routine Videos.** Action localization methods are moving from using simple pre-defined action labels [7, 17] to more complex natural language action descriptions [5, 36, 48]. Our goal is also to localize natural language descriptions of actions in videos. An important difference between our task and previous work is that the natural language descriptions come from the people filming the actions.

Research work such as [2, 36] also take advantage directly of the actions extracted from the transcripts, however their videos are instructional videos. Instead of looking at instructional videos, we choose a broader category: routine videos, which can contain instructions, but are more focused on describing the typical day of a person.

Compared to instructional videos, routine videos contain a more diverse set of activities, from waking up in the morning and taking a shower, to working out and making a meal. This diversity of actions in one video translates to many more diverse filming perspectives in the same video, which presents a novel challenge for action localization models. Another difference is that routine videos contain higher-level actions that can be abstract in nature (e.g., “wind down,” “go for a walk”) and thus harder to ground than clear instructions. This is an important difference, as it presents a challenge that is essential for webly supervised systems, which are expected to learn from a diverse mix of both concrete actions and high-level abstract actions. In the realm of web videos, instructional videos account for only a small fraction.

Finally, note that existing action localization methods by and large rely on simplifying assumptions (e.g., instructional videos, always visible actions, non-overlapping actions). In contrast, our paper introduces an evaluation that accounts for the additional challenges encountered in online videos.

### 3 DATA COLLECTION AND ANNOTATION

We collect a dataset of routine and do-it-yourself (DIY) videos from YouTube, consisting of people performing daily activities, such as making breakfast or cleaning the house. These videos also typically include a detailed verbal description of the actions being depicted. We choose to focus on these lifestyle vlogs because they are very popular, with tens of millions having been uploaded on YouTube; Table 1 shows the approximate number of videos available for several routine queries. Vlogs also capture a wide range of everyday activities; on average, we find thirty different visible human actions in five minutes of video.

By collecting routine videos, instead of searching explicitly for actions, we do implicit data gathering, a form of data collection introduced by Fouhey et al [13]. Because everyday actions are common and not unusual, searching for them directly does not return many results. In contrast, by collecting routine videos, we find many everyday activities present in these videos.

#### 3.1 Data Gathering

We build a data gathering pipeline (see Figure 2) to automatically extract and filter videos and their transcripts from YouTube. The input to the pipeline is manually selected YouTube channels. Ten channels are chosen for their rich routine videos, where the actor(s) describe their actions in great...
| Query                      | Results |
|----------------------------|---------|
| my morning routine         | 28M+    |
| my after school routine    | 13M+    |
| my workout routine         | 23M+    |
| my cleaning routine        | 13M+    |
| DIY                       | 78M+    |

Table 1. Approximate number of videos found when searching for routine and do-it-yourself queries on YouTube.

|                              |         |
|------------------------------|---------|
| Videos                       | 171     |
| Video hours                  | 20      |
| Transcript words             | 302,316 |
| Clips                        | 1,246   |
| Actions                      | 13,380  |
| Visible actions              | 3,131   |
| Non-visible actions          | 10,249  |

Table 2. Data statistics

Fig. 2. Overview of the data gathering pipeline.

detail. From each channel, we manually select two different playlists, and from each playlist, we randomly download ten videos. The following data processing steps are applied:

Transcript Filtering. Transcripts are automatically generated by YouTube. We filter out videos that do not contain any transcripts or that contain transcripts with an average (over the entire video) of less than 0.5 words per second.

These videos do not contain detailed action descriptions so we cannot effectively leverage textual information.

Extract Candidate Actions from Transcript. Starting with the transcript, we generate a noisy list of potential actions. This is done using the Stanford parser [8] to split the transcript into sentences and identify verb phrases, augmented by a set of hand-crafted rules to eliminate some parsing errors. The resulting actions are noisy, containing phrases such as “found it helpful if you” and “created before up the top you.”

Segment Videos into Clips. The length of our collected videos varies from two minutes to twenty minutes. To ease the annotation process, we split each video into clips (short video sequences...
of maximum one minute). Clips are split to minimize the chance that the same action is shown across multiple clips. This is done automatically, based on the transcript timestamp of each action. Because YouTube transcripts have timing information, we are able to line up each action with its corresponding frames in the video. We sometimes notice a gap of several seconds between the time an action occurs in the transcript and the time it is shown in the video. To address this misalignment, we first map the actions to the clips using the time information from the transcript. We then expand the clip by 15 seconds before the first action and 15 seconds after the last action. This increases the chance that all actions will be captured in the clip.

**Motion Filtering.** We remove clips that do not contain significant movement. We sample one out of every one hundred frames of the clip, and compute the 2D correlation coefficient between these sampled frames. If the median of the obtained values is greater than a certain threshold (we choose 0.8), we filter out the clip.

Videos with low movement tend to show people sitting in front of the camera, describing their routine, but not acting out what they are saying. There can be many actions in the transcript, but if they are not depicted in the video, we cannot leverage the video information.

### 3.2 Visual Action Annotation

We start by identifying which of the actions extracted from the transcripts are visually depicted in the videos. We create an annotation task on Amazon Mechanical Turk (AMT) to identify actions that are visible. We give each AMT turker a HIT consisting of five clips with up to seven actions generated from each clip. The turker is asked to assign a label (visible in the video; not visible in the video; not an action) to each action. Figure 4 shows the AMT interface used. Because it is difficult to reliably separate not visible and not an action, we group these labels together. Each clip is annotated by three different turkers. For the final annotation, we use the label assigned by the majority of turkers, i.e., visible or not visible / not an action.

To help detect spam, we identify and reject the turkers that assign the same label for every action in all five clips that they annotate. Additionally, each HIT contains a ground truth clip that has been pre-labeled by two reliable annotators. Each ground truth clip has more than four actions with labels that were agreed upon by both reliable annotators. We compute accuracy between a turker’s answers and the ground truth annotations; if this accuracy is less than 20%, we reject the HIT as spam.

After spam removal, we compute the agreement score between the turkers using Fleiss kappa [12]. Over the entire data set, the Fleiss agreement score is 0.35, indicating fair agreement.
seems like an eternity in the oven dehydrated at that point which pull it right off the baking sheet
take the tray out
...
Is the action visible in the video?

Fig. 4. Annotation tool used by Amazon Mechanical Turk workers to annotate if an action is visible or not in the video.

| Action | #1 | #2 | #3 | GT |
|--------|----|----|----|----|
| make sure your skin  | ✗  | ✗  | ✓  | ✗  |
| cleansed before you  | ✓  | ✓  | ✓  | ✓  |
| do all that          | ✗  | ✗  | ✓  | ✗  |
| absorbing all that serum | ✗  | ✗  | ✓  | ✗  |
| move on              | ✗  | ✗  | ✗  | ✗  |

Fig. 5. An example of low agreement. The table shows actions and annotations from workers #1, #2, and #3, as well as the ground truth (GT). Labels are: visible - ✓, not visible - ✗. The bottom row shows screenshots from the video. The Fleiss kappa agreement score is -0.2.

Fig. 6. Action temporal localization annotation. Each action is localized in the video according to its start and end time offsets. The action is localized according to its visibility in the video, and if it cannot be seen, it is marked as not visible.

the ground truth data, the Fleiss kappa score is 0.46, indicating moderate agreement. This fair to moderate agreement indicates that the task is difficult, and there are cases where the visibility of the actions is hard to label. To illustrate, Figure 5 shows examples where the annotators had low agreement. Table 2 shows statistics for our final dataset of videos labeled with actions, and Figure 3 shows a sample video and transcript, with annotations.

Note that the goal of our dataset is to capture naturally-occurring, routine actions. Because the same action can be identified in different ways (e.g., “pop into the freezer”, “stick into the freezer”),
Table 3. Comparison between our dataset and other video human action recognition datasets. # Actions show either the number of action classes in that dataset (for the other datasets), or the number of unique visible actions in that dataset (ours); # Verbs shows the number of unique verbs in the actions; Implicit is the type of data gathering method (versus explicit); Label types are either post-defined (first gathering data and then annotating actions): √, or pre-defined (annotating actions before gathering data): x.

| Dataset       | #Actions | #Verbs | #Actors | Implicit | Label types |
|---------------|----------|--------|---------|----------|-------------|
| Ours          | 4340     | 580    | 10      | ✓        | ✓           |
| VLOG [13]     | -        | -      | 10.7k   | ✓        | ✓           |
| Kinetics [26] | 600      | 270    | -       | x        | x           |
| ActivityNet [6] | 203    | -      | -       | ✓        | x           |
| MIT [39]      | 339      | 339    | -       | x        | x           |
| AVA [20]      | 80       | 80     | 192     | ✓        | x           |
| Charades [50] | 157      | 30     | 267     | x        | x           |
| MPII Cooking [46] | 78    | 78     | 12      | ✓        | x           |

our dataset has a complex and diverse set of action labels. These labels demonstrate the language used by humans in everyday scenarios; because of that, we choose not to group our labels into a pre-defined set of actions. Table 3 shows the number of unique verbs, which can be considered a lower bound for the number of unique actions in our dataset. On average, a single verb is used in seven action labels, demonstrating the richness of our dataset.

The action labels extracted from the transcript are highly dependent on the performance of the constituency parser. This can introduce noise or ill-defined action labels. Some actions contain extra words (e.g., “brush my teeth of course”), or lack words (e.g., “let me just”). Some of this noise is handled during the annotation process; for example, most actions that lack words are labeled as “not visible” or “not an action” because they are hard to interpret.

### 3.3 Temporal Action Annotation

Each video is associated with a set of human actions, in the form of verb phrases extracted from the automatically generated video transcripts. The actions are labeled into two categories: visible or not visible, depending on whether the actions are explicitly represented in the video. For example, in the video sequence shown in Figure 1, the action “drink coffee” is not visible in the video; it is only mentioned as a reason for performing the visible action of “use a melatonin spray.” Other not visible actions from Figure 1 are: “help,” “hope,” “enjoyed this video,” “thumbs it up” and “subscribe,” which relate to video feedback but are not visually shown.

Two of the authors of this paper annotated the start and end time of all the visible actions in the dataset, as illustrated in Figure 6. Each action is localized according to its start and end time offsets. The timestamp is marked according to when the action is visible, which does not necessarily correspond to when it is talked about. If the annotators were not able to localize the action in the clips, they marked it as not visible, which corresponds to a correction of the original dataset [24]. They performed the annotations using a simple annotation tool that we built for this purpose, which is publicly available at https://github.com/OanalGnat/video_annotations.

We measure the inter-annotator agreement by computing the Krippendorff’s Alpha score [27] using the interval difference function for each video. We obtain scores between 0.78 and 0.90, which indicate a high agreement.
Table 4. Statistics for the experimental data split. “Vis.” is the percentage of visible actions among the narrated actions.

|        | #actions | Vis. (%) | #videos | #clips |
|--------|----------|----------|---------|--------|
| Train  | 4,939    | 35.1     | 110     | 680    |
| Val    | 1,264    | 35.9     | 26      | 187    |
| Test   | 3,456    | 25.7     | 35      | 275    |

Table 5. Action duration analysis: (a) Distribution in our dataset; (b) Example of long and short actions, each with a sample object, grouped by verbs and sorted by verb frequency; (c) Percentage of long (>15s) actions in other datasets.

| Duration (s) | #actions |
|--------------|----------|
| 0-5          | 1,136    |
| 5-15         | 1,200    |
| 15-25        | 475      |
| 25-35        | 157      |
| 35-45        | 72       |
| 45-60        | 99       |

| Long actions | #actions |
|--------------|----------|
| use (a whisk)| 87       |
| make (oatmeal)| 81      |
| clean (my skin)| 60     |

| Short actions | #actions |
|---------------|----------|
| add (spice)  | 362      |
| use (the clamps)| 228   |
| put (a lid on top)| 179   |

| Dataset      | Long actions (%) |
|--------------|------------------|
| Charades-STA [14] | 4.2            |
| CrossTask [64]     | 16.4           |
| COIN [54]          | 31.6           |
| Ours               | 25.5           |

For our experiments, we split the data by vlog channel. Out of ten channels, six channels are used for training, two channels for validation, and two for testing. Statistics for this experimental split are shown in Table 4.

3.4 Data Analysis

We perform two types of analyses to gain a better understanding of our dataset.

Action Duration.

First, we measure the distribution of action durations in our dataset. As shown later, this information is important, as the action durations can have an impact on the performance of different models. Table 5a shows the action duration distribution in the dataset. A summary of long actions found in other datasets is shown in Table 5c (we define an action as long if it exceeds fifteen seconds). Table 5b shows examples of long actions, grouped by verb and sorted by frequency.

Temporal Relations between Actions.

Second, we analyze the temporal relations between actions mentioned in the transcripts. These actions can be challenging to model as they capture the complexities of real life. While there are
several actions that follow each other (as more naturally expected), there are also actions that overlap, are included in one another, or even happen at the same time. From a total of 2,070 number of overlapping actions, 1,573 are included in each other and 269 occur exactly at the same time. Table 6 shows examples of such actions. While several action localization datasets have been proposed in the past [54], to the best of our knowledge, this dataset is the only action localization dataset that contains overlapping actions, making it challenging and novel. For the purpose of this work, we localize each action independent of other actions, but future work may leverage the relations that exist between actions.

### 4 TWO-STAGE ACTION LOCALIZATION

For a given action mentioned in a video transcript, our goal is to: (1) decide if it is visible within the video clip; and (2) if it is visible, identify its temporal location (i.e., the time interval start and end times).

To achieve this goal, we propose a two-stage method which we call 2Seal (2-StagE Action Localization).

Figure 7 shows the overall architecture of 2Seal. Following our analysis of the variation in action duration (see Section 3.4), and empirical observations made on the development dataset, we hypothesize that shorter actions can be localized mainly based on the temporal information inferred from the transcript (i.e., when an action was narrated within the transcript), whereas longer actions are often temporally shifted with respect to their mention in the transcript and thus can benefit from a multimodal model. We thus devise an architecture that first aims to predict whether the action is short or long, and correspondingly activates a transcript alignment (for short actions) or a multimodal model (for long actions). We describe below each of these main components.

**Action Duration Classification** We use the annotated temporal locations in the videos to determine the expected duration of each action, and build a binary classifier to discriminate between short (≤15s) and long (>15s) actions. We choose this threshold based on the validation data. The classifier uses as input an action text embedding obtained from a text encoder, as described in Section 5.
Inputs: untrimmed clip (~ 1min)

Generate overlapping 3s spans: 

(action mentions extracted from the video transcript):

- a₁: "brushing my teeth"
- a₂: "hop into bed"
- a₃: "have caffeine"
- a₄: "use a melatonin spray"
- a₅: "fall asleep"

SVM: action length classification

Transcript alignment

Multimodal model

Fig. 7. 2SEAL method architecture. Note the depicted MPU-based multimodal model can be replaced with any multimodal model. The MPU model is composed of vector element-wise addition (‘+’), vector element-wise multiplication (‘x’) and vector concatenation followed by a Fully Connected (‘FC’) layer to combine the information from both textual and visual modalities.

Fig. 8. Example of applying the Transcript Alignment method. The transcript contains time intervals for utterances. Each action contained in an utterance is assigned the corresponding time interval.

**Transcript Alignment.** Each video contains a transcript automatically generated by the YouTube API. The transcript contains time information for every utterance. Given an action mention extracted from an utterance, the Transcript Alignment method assumes the action is visible, and predicts its temporal location to be the time interval associated with the corresponding utterance, as illustrated in Figure 8. The transcript alignment is also illustrated in Figure 7.

**Multimodal Model.** We split the video clips into fixed-duration spans and convert the action temporal localization task into binary classification tasks based on the output from a scorer model \( s \). We aim to predict if the visual information from a video clip span corresponds to the linguistic
When Did It Happen? Duration-informed Temporal Localization of Narrated Actions in Vlogs

| Method               | A    | P    | R    | F1   |
|----------------------|------|------|------|------|
| Majority             | 74.4 | 74.4 | 100.0| 85.3 |
| Action Duration Clf. | 80.6 | 81.8 | 97.6 | 89.0 |

Table 7. Action duration classification results on the validation set. The classification is binary, where the positives are the short actions (≤15s) and the negatives the long ones (>15s). The columns are in order: accuracy (A), precision (P), recall (R) and F1 score (F1).

representation of an action. For a given action mention within the transcript and a fixed-duration video clip span, we compute a similarity score to decide if they correspond to each other. The action mention is represented using a text encoder and the features for the video clip span are obtained from a video encoder (see Section 5).

The process of pairing action mentions to video clip spans is shown in Figure 7; s can be represented by any multimodal model, and we describe several models in Section 5.2. At test time, given a video clip and its corresponding transcript, we input all the pairs of action mentions and fixed-duration video clip spans. We merge all the spans that surpass a certain threshold and are separated by less than three seconds into proposals. Each proposal is assigned the maximum similarity score of its spans. We then perform non-maximum suppression to select the best proposal as the predicted action location interval. At training time, we focus only on the binary task and train s with the standard cross-entropy loss. Given that an action mention has many more negative (not visible) fixed-duration video clip spans in a given video clip, we balance the classes out via downsampling by taking negative random samples from the same video clip. The question of how different negative sampling strategies affect the scorer model performance is left for future work.

5 EXPERIMENTS

To evaluate our duration-informed action localization method, we run several comparative experiments on the dataset described in Section 3. We compare our method with several strong baselines, and also perform feature ablation and a breakdown of results by action duration.

In all our experiments, we use a video encoder consisting of the last layer (mixed_5c) from a Kinetics [7] pre-trained I3D model. The video clips are divided into overlapping three-second spans with a stride of 1s. We freeze both the text and the video encoders and take their outputs as features. For the Action Duration Classification, we use an SVM classifier with C=1.0 and an RBF kernel, and weight the samples inversely proportional to their class frequency. We train the models using an Adam optimizer with early stopping (tolerance 15 epochs), with a learning rate of 0.001 and a batch size of 64.

5.1 Action Duration Classification.

We train the action duration classifier described in the previous section using only the visible actions. The results are reported in Table 7. For comparison, we also show the performance of a majority classifier, which labels every action as "short" by default. As shown in the table, despite the simplicity of the classifier, the action duration classifier obtains good improvement over the majority baseline.

5.2 Temporal Action Localization

Our 2Seal method includes a scorer that measures the similarity between a video clip and an action mention (see Figure 7). To implement this scorer, we experiment with three methods proposed in...
previous work: multimodal processing unit, multiple instance learning noise contrastive estimation, and stacked cross attention.

**Multimodal Processing Unit (MPU).** We use the MPU model [14] to compute the similarity score between the language representation of a narrated action and a video clip span. For the text features, we fine-tune a pre-trained BERT-base-uncased [9] for domain adaption by on 884 vlog transcripts with 80,749 sentences. We take embeddings from this model for the action mentions in the transcripts by average pooling (the final embedding size is 768). In Section 6.2 we experiment with variations of this text encoder. The text and visual features for each pair are linearly mapped to the same embedding space. Next, the MPU model is applied to compute the interaction between the two vectors of the same duration. The MPU model is composed of vector element-wise addition (‘+’), vector element-wise multiplication (‘x’) and vector concatenation followed by a Fully Connected (‘FC’) layer to combine the information from both textual and visual modalities. The outputs from all three operations are concatenated to construct a multi-modal representation. This process is also illustrated in the overall architecture in Figure 7. The resulting representation is given as input to a linear layer and finally to a sigmoid function to obtain a similarity score.

**Multiple Instance Learning Noise Contrastive Estimation (MIL-NCE).** We use the MIL-NCE model from [35] which was trained on HowTo100M [36]. The similarity score is computed as a dot product between the text and video encoder outputs. The text encoder takes embeddings from a GoogleNews-pretrained skipgram word2vec [37] implementation and further processes and pools the embeddings to obtain a fixed-size representation. We use the MIL-NCE I3D\(^1\) visual features, and not the S3D features, for consistency reasons and to ensure a fair comparison between the multimodal models. We empirically find it beneficial to threshold the similarities at mid-range value after experimenting with linear regression models on the validation data. Note we do not fine-tune this model but freeze it. Future work can explore how the method benefits from fine-tuning.

**Stacked Cross Attention (SCA).** We also experiment with the SCA method [29], and adapt its Text-Image formulation. It first attends to image frames with respect to each word, and then compares each word to its corresponding attended frame vector to determine the importance of each word. The relevance \(R\) between the \(i\)-th word and the image is defined as the cosine similarity between the \(i\)-th word vector \(v_i\) and its attended frame vector \(a^i_I\). The final similarity score between image \(I\) and sentence \(T\) is summarized by average pooling: \(S'_{AVG}(I, T) = \frac{1}{n} \sum_{j=1}^{n} R'(e_j, a^j_I)\). The textual features are represented using a Gated Recurrent Unit (GRU) [19] as in [29]. We use the mid-range threshold for the similarity score.

**2D Temporal Adjacent Networks (2D-TAN).** We find the 2D-TAN model [63] suitable for our task as it is built to localize multiple natural language queries in a video.

The video clips are represented using C3D [55] features and the action queries using GloVe [42] embeddings, as described in the 2D-TAN paper [63]. We take as final proposal the action localization proposal with the highest score.

We test the pre-trained model and also fine-tune it on our training and validation data. We run two model configurations, which were trained on TACoS [45], namely “Pool” and “Conv” in our test set. “Pool” and “Conv” represent max-pooling and stacked convolution respectively, which indicates two different ways for moment feature extraction in the 2D-TAN model. We report the results of fine-tuned “Conv” 2D-TAN model, which is the best performing 2D-TAN model configuration on our test dataset.

\(^1\)https://tfhub.dev/deepmind/mil-nce/i3d/1
Results

We evaluate the predictions made by the action localization methods using two evaluation metrics. First, we compute the Visibility Accuracy (VA) to decide if the method can distinguish between visible and not visible actions. Second, only for the visible actions, we compute the recall at different Intersection over Union (IoU) thresholds: 0.1, 0.3, 0.5 and 0.7. A higher threshold means a stronger constraint on how exact the match between the predicted and the ground truth location needs to be. If the predicted interval has an IoU score with the ground truth greater than the threshold, we consider the prediction as being correct. We also compute the average recall over all IoU values, as the mIoU. Note that if a method predicted that a visible action is non-visible, then the recall score is penalized.

Table 8 presents the temporal action localization results on our data. The Transcript Alignment method performs better than the MPU, MIL-NCE, SCA and 2D-TAN methods if we do not previously apply our proposed 2Seal method before. However, when using our 2Seal method that combines both the Transcript Alignment and a method to score long actions (either MPU, MIL-NCE, SCA, or 2D-TAN), the performance improves significantly, with the system integrating the MPU model leading to the best results. We suspect MIL-NCE may perform better if fine-tuned, however our intention is not to compare MPU and MIL-NCE but to show how our method can improve over other existing methods. The results confirm our initial hypothesis that actions of different duration benefit from different methods: the transcript alignment excels at short actions, while the multimodal model performs better for long actions.

Analyses and Discussion

To gain insights into the performance of our proposed model in relation to action duration, and to understand the role played by different features, we perform several analyses.
### 6.1 Action Duration Impact

If the action is brief, the IoU metric will be influenced by a few seconds compared to when the action is longer in duration. This metric penalizes more the mislocalization of short actions, as compared to the longer ones. This analysis is often done for the task of object detection, where the IoU scores are grouped by bounding box size [44]. To verify our initial hypothesis that actions of different duration benefit from different localization methods, we break down the results of the MPU (the best scorer from among MPU, MIL-NCE, SCA and 2D-TAN without applying the 2SEAL method) by action duration in Table 9. As shown in the table, the performance of the model is connected to the duration of the actions. For long actions, the multimodal method obtains better results compared to the transcript alignment method, while the opposite is true for short actions.

### 6.2 Text and Visual Features

In Table 10, we experiment with the MPU model (without applying the 2SEAL method) and look into how each modality contributes to solving this task, by removing one modality at a time from our best performing model. We also analyze other types of text embeddings. Inspired by [40, 49], we focus on verbs and nouns, which we extract from the actions and compute their BERT embeddings. We observe that the visual information contributes the most to the task of action localization, as
Table 10. Results on the test set for different variations of the input to the MPU model. “DA” stands for Domain Adaptation.

removing this information drastically lowers the model performance. Another observation is that processing the entire action is more beneficial to the model than focusing only on nouns and verbs.

6.3 Qualitative Results

Randomly sampled results are shown in Figure 9. They are grouped by the different levels of action overlapping: no overlap, intersection, inclusion and perfect overlap. From analyzing these results, a future work direction emerges: detecting which actions are likely to happen at the same time, which in turn can lead to better algorithms for action localization.

7 CONCLUSION

In this paper, we introduced a new dataset for action localization in vlogs — a growing form of online video communication where everyday routine actions are described in language and also presented visually. Using this dataset, we addressed the task of temporal action localization in videos. We proposed 2Seal – a simple yet effective method to visually localize the actions mentioned in a video transcript, which relies on both language and vision, and specifically accounts for the duration of an action for the purpose of building a more accurate system.

Through several extensive evaluations, we showed that our method improves and complements other methods by first computing the expected duration of an action, and selectively applying a language-based or multimodal model depending on the action duration. This work contributes to the larger body of work for multimodal understanding, and at the same time builds a large repository of vision-language representations covering a wide spectrum of actions that can be used for downstream tasks such as action recognition systems, human behavior understanding, event recognition, and others. The dataset introduced in this paper, the annotation tool, and the system code are publicly available at https://github.com/MichiganNLP/vlog_action_localization.

8 ACKNOWLEDGMENTS

We thank Weiji Li for his help with the human annotations of action visibility. This research was partially supported by a grant from the Automotive Research Center (ARC) at the University of Michigan in accordance with Cooperative Agreement W56HZV-19-2-0001.
REFERENCES

[1] Sami Abu-El-Haija, Nisarg Kothari, Joonseok Lee, Paul Natsev, George Toderici, Balakrishnan Varadarajan, and Sudheendra Vijayanarasimhan. 2016. Youtube-8m: A large-scale video classification benchmark. arXiv preprint arXiv:1609.08675 (2016).

[2] Jean-Baptiste Alayrac, Piotr Bojanowski, Nischant Agrawal, Josef Sivic, Ivan Laptev, and Simon Lacoste-Julien. 2016. Unsupervised learning from narrated instruction videos. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 4575–4583.

[3] Peter Anderson, Xiaodong He, Chris Buehler, Damien Teney, Mark Johnson, Stephen Gould, and Lei Zhang. 2018. Bottom-up and top-down attention for image captioning and visual question answering. In Proceedings of the IEEE conference on computer vision and pattern recognition. 6077–6086.

[4] Lisa Anne Hendricks, Oliver Wang, Eli Shechtman, Josef Sivic, Trevor Darrell, and Bryan Russell. 2017. Localizing Moments in Video With Natural Language. In The IEEE International Conference on Computer Vision (ICCV).

[5] Lisa Anne Hendricks, Oliver Wang, Eli Shechtman, Josef Sivic, Trevor Darrell, and Bryan Russell. 2017. Localizing moments in video with natural language. In Proceedings of the IEEE international conference on computer vision. 5803–5812.

[6] Fabian Caba Heilbron, Victor Escorcia, Bernard Ghanem, and Juan Carlos Niebles. 2015. Activitynet: A large-scale video benchmark for human activity understanding. In Proceedings of the ieee conference on computer vision and pattern recognition. 961–970.

[7] Joao Carreira and Andrew Zisserman. 2017. Quo vadis, action recognition? a new model and the kinetics dataset. In proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 6299–6308.

[8] Danqi Chen and Christopher Manning. 2014. A fast and accurate dependency parser using neural networks. In Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP). 740–750.

[9] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In NAACL-HLT.

[10] Jeffrey Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, and Trevor Darrell. 2015. Long-term recurrent convolutional networks for visual recognition and description. In Proceedings of the IEEE conference on computer vision and pattern recognition. 2625–2634.

[11] Victor Escorcia, Mattia Soldan, Josef Sivic, Bernard Ghanem, and Bryan Russell. 2019. Temporal Localization of Moments in Video Collections with Natural Language. arXiv preprint arXiv:1907.12763 (2019).

[12] Joseph L Fleiss and Jacob Cohen. 1973. The equivalence of weighted kappa and the intraclass correlation coefficient as measures of reliability. Educational and psychological measurement 33, 3 (1973), 613–619.

[13] David F Fouhey, Wei-cheng Kuo, Alexei A Efros, and Jitendra Malik. 2018. From lifestyle vlogs to everyday interactions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 4991–5000.

[14] Jiyang Gao, Chen Sun, Zhenheng Yang, and Ram Nevatia. 2017. Tall: Temporal activity localization via language query. In Proceedings of the IEEE International Conference on Computer Vision. 5267–5275.

[15] Runzhou Ge, Jiyang Gao, Kan Chen, and Ram Nevatia. 2019. MAC: Mining Activity Concepts for Language-based Temporal Localization. In 2019 IEEE Winter Conference on Applications of Computer Vision (WACV). IEEE, 245–253.

[16] Soham Ghosh, Anuva Agarwal, Zarana Parekh, and Alexander Hauptmann. 2019. ExCL: Extractive Clip Localization Using Natural Language Descriptions. arXiv preprint arXiv:1904.02755 (2019).

[17] Rohit Girdhar, Joao Carreira, Carl Doersch, and Andrew Zisserman. 2019. Video action transformer network. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 244–253.

[18] Yash Goyal, Tejas Khot, Douglas Summers-Stay, Dhruv Batra, and Devi Parikh. 2016. Making the V in VQA Matter: Elevating the Role of Image Understanding in Visual Question Answering. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2016). 6325–6334.

[19] Alex Graves. 2008. Supervised Sequence Labelling with Recurrent Neural Networks. In Studies in Computational Intelligence.

[20] Chunhui Gu, Chen Sun, David A Ross, Carl Vondrick, Caroline Pantofaru, Yeqing Li, Sudheendra Vijayanarasimhan, George Toderici, Susanna Ricco, Rahul Sukthankar, et al. 2018. Ava: A video dataset of spatio-temporally localized atomic visual actions. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR). 6047–6056.

[21] Fabian Caba Heilbron, Victor Escorcia, Bernard Ghanem, and Juan Carlos Niebles. 2015. ActivityNet: A large-scale video benchmark for human activity understanding. 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015). 961–970.

[22] Lisa Anne Hendricks, Oliver Wang, Eli Shechtman, Josef Sivic, Trevor Darrell, and Bryan Russell. 2018. Localizing moments in video with temporal language. arXiv preprint arXiv:1809.01337 (2018).

[23] Drew A Hudson and Christopher D Manning. 2019. Gqa: a new dataset for compositional question answering over real-world images. arXiv preprint arXiv:1902.09506 (2019).
[50] Gunnar A Sigurdsson, Güil Varol, Xiaolong Wang, Ali Farhadi, Ivan Laptev, and Abhinav Gupta. 2016. Hollywood in homes: Crowdsourcing data collection for activity understanding. In European Conference on Computer Vision. Springer, 510–526.

[51] Alane Suhr, Stephanie Zhou, Ally Zhang, Iris Zhang, Huajun Bai, and Yoav Artzi. 2018. A corpus for reasoning about natural language grounded in photographs. arXiv preprint arXiv:1811.00491 (2018).

[52] Chen Sun, Austin Myers, Carl Vondrick, Kevin Murphy, and Cordelia Schmid. 2019. Videobert: A joint model for video and language representation learning. In Proceedings of the IEEE International Conference on Computer Vision. 7464–7473.

[53] Hao Tan and Mohit Bansal. 2019. Lxmert: Learning cross-modality encoder representations from transformers. arXiv preprint arXiv:1908.07490 (2019).

[54] Yansong Tang, Dajun Ding, Yongming Rao, Yu Zheng, Danyang Zhang, Lili Zhao, Jiwen Lu, and Jie Zhou. 2019. Coin: A large-scale dataset for comprehensive instructional video analysis. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 1207–1216.

[55] Du Tran, Lubomir Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. 2015. Learning Spatiotemporal Features with 3D Convolutional Networks. arXiv:1412.0767 [cs.CV]

[56] Du Tran, Lubomir D. Bourdev, Rob Fergus, Lorenzo Torresani, and Manohar Paluri. 2014. C3D: Generic Features for Video Analysis. ArXiv abs/1412.0767 (2014).

[57] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In NIPS.

[58] Heng Wang, Alexander Kläser, Cordelia Schmid, and Cheng-Lin Liu. 2011. Action recognition by dense trajectories. CVPR 2011 (2011), 3169–3176.

[59] Mingzhe Wang, Mahmoud Azab, Noriyuki Kojima, Rada Mihalcea, and Jia Deng. 2016. Structured matching for phrase localization. In European Conference on Computer Vision. Springer, 696–711.

[60] Zichao Yang, Xiaodong He, Jianfeng Gao, Li Deng, and Alexander J. Smola. 2015. Stacked Attention Networks for Image Question Answering. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2015), 21–29.

[61] Quanzeng You, Hailin Jin, Zhaowen Wang, Chen Fang, and Jiebo Luo. 2016. Image captioning with semantic attention. In Proceedings of the IEEE conference on computer vision and pattern recognition. 4651–4659.

[62] Yitian Yuan, Tao Mei, and Wenwu Zhu. 2018. To Find Where You Talk: Temporal Sentence Localization in Video with Attention Based Location Regression. ArXiv abs/1804.07014 (2018).

[63] Songyang Zhang, Houwen Peng, Jianlong Fu, and Jiebo Luo. 2020. Learning 2D Temporal Adjacent Networks for Moment Localization with Natural Language. In AAAI.

[64] Dimitri Zhukov, Jean-Baptiste Alayrac, Ramazan Gokberk Cinbis, David Fouhey, Ivan Laptev, and Josef Sivic. 2019. Cross-task weakly supervised learning from instructional videos. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 3537–3545.