

What, when, and where? - Self-Supervised Spatio-Temporal Grounding in Untrimmed Multi-Action Videos from Narrated Instructions

Brian Chen¹ Nina Shvetsova² Andrew Rouditchenko³ Daniel Kondermann⁴
 Samuel Thomas^{5,6} Shih-Fu Chang¹ Rogerio Feris^{5,6} James Glass³ Hilde Kuehne^{2,6}

¹Columbia University, ²Goethe University Frankfurt, ³MIT CSAIL, ⁴Quality Match GmbH,

⁵IBM Research AI, ⁶MIT-IBM Watson AI Lab

{bc2754, sc250}@columbia.edu, {shvetsov, kuehne}@uni-frankfurt.de, {roudi, glass}@mit.edu,
 dk@quality-match.com, {sthomas, rsferis}@us.ibm.com

Abstract

Spatio-temporal grounding describes the task of localizing events in space and time, e.g., in video data, based on verbal descriptions only. Models for this task are usually trained with human-annotated sentences and bounding box supervision. This work addresses this task from a multi-modal supervision perspective, proposing a framework for spatio-temporal action grounding trained on loose video and subtitle supervision only, without human annotation. To this end, we combine local representation learning, which focuses on leveraging fine-grained spatial information, with a global representation encoding that captures higher-level representations and incorporates both in a joint approach. To evaluate this challenging task in a real-life setting, a new benchmark dataset is proposed providing dense spatio-temporal grounding annotations in long, untrimmed, multi-action instructional videos for over 5K events. We evaluate the proposed approach and other methods on the proposed and standard downstream tasks showing that our method improves over current baselines in various settings, including spatial, temporal, and untrimmed multi-action spatio-temporal grounding.

1. Introduction

Spatio-temporal grounding (STG) involves the challenging process of locating events in space and time within video data which utilizes text referential expressions as input. To this end, methods usually need to train on a combination of spatio-temporal bounding box annotation, together with a human-generated caption, describing the visual content of the bounding box [46, 17]. Compared to that, multimodal self-supervised learning tries to leverage “free” data sources, such as video and respective automatic speech recognition (ASR) captions from large-scale instruc-



Figure 1: **Learning Spatio-temporal grounding in untrimmed videos:** In training, we learn from unlabeled videos without human annotation. In evaluation, we perform spatio-temporal grounding using an action description such as “crack egg” as a query. The model needs to localize both the action’s temporal boundary and spatial region in the long untrimmed video. We visualize the heat-map from the annotation points as well as derived bounding boxes.

tional videos to learn representations without human annotation [28, 27, 4, 3, 7]. Beyond achieving state-of-the-art performance on various tasks after fine-tuning, the resulting models also show great capabilities for zero-shot tasks such as cross-modal video retrieval or classification and also allow for zero-shot temporal action segmentation and detection based on free text queries [54, 20, 39, 7, 35].

Beyond that, other approaches show label-free spatial grounding from multimodal data, mainly image-caption [2, 47, 22, 42, 51] or video-caption pairs [38, 34]. Here, the goal is to correctly localize a referential expression in an image or each video frame, e.g., via a bounding box or a heatmap. But the assumption is that the evaluated expression is visible in the image or all video frames. Those methods are thus not optimized to detect whether an event is present in a video.

The following work aims to bring together those ideas to address the task of spatio-temporal action grounding from multimodal supervision in untrimmed videos, proposing a grounding approach that uses video-text pairs based on ASR transcripts in instructional videos and learns the spatial representation of free-text events as well as their temporal extent as shown in Figure 1. To this end, we leverage two different representations of the visual data: a global feature representation based on full-frame information to define the temporal extent of an event and a local representation based on frame-wise grid features for spatial localization. The motivation for this dualism is that while the local representation captures the spatial correlations between vision and text input, this can be too fine-grained to learn a holistic representation of the frame, while the global representation can be assumed to capture a more compact, aggregated view compared to local data and thus to provide a more reliable cue for the task of temporal localization. However, compared to the clean video-caption setup of most spatio-temporal grounding methods, the ASR text can be noisy as not all comments refer to visible events. Further, as there is only a loose temporal correlation, the described activities might not be precisely aligned, can be scattered over multiple frames, or not be present at all [27, 14]. Therefore, we propose to specifically select frames to capture only those useful for training. To this end, we look for frames that actually match the vocabulary of the respective text, leveraging a selection strategy by Sinkhorn optimal transport [9]. This allows us to train a model that can localize action instructions and semantic concepts in space and time within videos without labeling supervision.

To evaluate spatio-temporal grounding in untrimmed videos, a new benchmark, GroundingYouTube, is proposed. It is based on the existing MiningYouTube dataset [20] and extended with spatio-temporal localization information. This setup differs from other benchmarks [38, 8, 52] in two ways: first, it focuses on the spatio-temporal grounding of referential actions instead of objects; second, the dense annotations on multi-action in the video allow us to benchmark action grounding in long, realistic untrimmed videos compared to existing, often pre-clipped benchmarks [8, 49]. The benchmark provides queries for 512 different event types throughout the entire data, resulting in over 5K spatio-temporal annotations as shown in Figure 1.

To evaluate the proposed approach as well as the new benchmark, the system is trained on the HowTo100M dataset [28] and compared to state-of-the-art methods based on full, weak, and self-supervision for spatial and temporal, as well as combined spatio-temporal grounding tasks. It shows that existing methods usually do well in one of the two aspects, spatial or temporal grounding. In contrast, the proposed method can combine spatial and temporal aspects of semantic concepts without label annotation.

We summarize the contributions of this work as follows¹: (1) We propose a framework for spatio-temporal grounding in untrimmed videos based on weakly aligned multimodal supervision without human annotation. We employ a combination of global representation learning to encode temporal information and local representations to learn the spatio-temporal extent of actions in instructional videos. (2) To facilitate this task, we propose a frame selection strategy based on Sinkhorn-Knopp Optimal transport that improves the quality of the acquired learning samples, leading to more effective supervision. (3) We provide a new benchmark and annotations to evaluate this challenging problem on real-world multi-action instructional video data.

2. Related Work

2.1. Supervised Spatio-temporal Grounding.

Spatio-temporal Grounding refers to the problem of localizing a sequence of bounding boxes (a spatio-temporal tube) for a target object described by an input text. This problem has been addressed by various approaches TubeDETR [46], STCAT [17], STVGBert[37], STVGBert[37], STGVT [40], STGRN[49]. These methods rely on proposal networks such as Faster R-CNN[32] or MDETR [19] to predict bounding box coordinates for learning text-to-region interaction. All those approaches rely on supervised training with the human-annotated sentence and bounding box supervision, provided, e.g., by datasets such as VidSTG [49] and HC-STVG[8]. While those datasets provide a temporal aspect, temporal detection is usually limited to identifying the start and end frame of a single action in a video. Compared to that, an untrimmed setting usually comprises multiple actions in a longer video that can be separated by longer background sequences. This conceptually differs from previous works [8] that typically use short videos of around 5-10 seconds.

2.2. Multimodal Self-supervised Learning.

The field of multimodal self-supervised learning aims to learn data representations by leveraging large amounts of unlabeled data with multiple modalities. Early works [44, 10] started by projecting images and text into a joint visual-language embedding space, where embeddings of

¹We will make the code and the annotations publicly available.

semantically-similar pairs are close. Those ideas have now grown into systems such as CLIP [30] based on representations from 400 million internet image-text pairs, or MIL-NCE [27] using the HowTo100M dataset [28] to train a video-language embedding space from 1.2 million instructional videos paired with text descriptions from ASR. Follow-up works [4, 3, 33, 7, 35] show that using videos without annotation enables an effective multimodal embedding space via contrastive learning.

Based on those advantages, approaches started to address the problem of **Spatial Video Grounding** from multimodal self-supervised aiming to identify spatial locations in a *trimmed* video based on text descriptions without the need for bounding box annotation during training. One of the early works studied this task in the context of weakly supervised learning scenarios where we learn grounding with human-annotated captions of the video [52]. In this context, works [38, 34] have focused on object grounding benchmarks such as YouCook2-BoundingBox [53], which provides bounding box annotations for visible objects in cooking videos. Other works such as GLIP[22] and RegionCLIP[51] combine the principles of large-scale vision language training with bounding box fine-tuning on object detection datasets[12, 25]. Recently, the YouCook-Interactions dataset [38] and CoMMA[38] have been proposed for the spatial grounding of objects and actions with multimodal self-supervision from HowTo100M videos. All these works assume that the video is temporally clipped with respect to the grounding phrase.

Compared to that, **Temporal Video Grounding** aims to determine the set of consecutive frames corresponding to a text query in an *untrimmed* video [31, 16, 15, 36], thus predicting temporal boundaries of action instances. Recent work such as MIL-NCE [27], MCN [7], and VideoCLIP [24] utilize large-scale pretraining for grounding actions temporally via text-to-frame similarity matching on video datasets such as MiningYouTube [20] or CrossTask [54] without proposals. However, the majority of methods neglect the word-to-spatial relation and lack spatial localization ability [48, 50]. To address this limitation, we propose a novel approach that utilizes large-scale pretraining for grounding actions by leveraging word-to-spatial relations and improving spatial localization ability.

3. A Global-Local Framework for STG

3.1. General setup

The goal of the proposed method is to temporally and spatially localize actions based on free-text queries in untrimmed videos. To this end, two representation spaces should be learned from unlabeled videos, a local and a global one. We start with narrated video clips, each associated with a corresponding visual representation and text nar-

ration. Given this input, the text-video embedding spaces for both global and local representations are learned via contrastive loss by bringing the embeddings of semantically similar visual and text content closer together for both representations. Namely, for each clip $\mathcal{X} = \{\mathcal{V}, \mathcal{S}\}$, let \mathcal{V} stand for the video clip and \mathcal{S} for the text narration sentence generated by the automatic speech recognition (ASR) system. Each clip \mathcal{V} consists of $T \times N$ spatio-temporal tokens $\{v_{t,n}\}$, where $t \in \{1, \dots, T\}$ represents the number of frames in the video and $n \in \{1, \dots, N\}$ represents the number of spatial grid region tokens or features in a frame. The text sentence \mathcal{S} consists of K words $\{s_1, \dots, s_K\}$. We represent localized features by the tokens from each modality, and the global features $\{V, S\}$ are acquired either by mean-pooling over the local features or by using the classifier token from the transformer as in [30]. We learn transformations $f : V \rightarrow \mathbb{R}^d$ to a d -dimensional representation $f(V) \in \mathbb{R}^d$ from the global representation V , and $g : S \rightarrow \mathbb{R}^d$, to produce similar d -dimensional text global embeddings: $g(S) \in \mathbb{R}^d$. Similar to $\{f, g\}$, we note $\{f', g'\}$ to be the transform for localized features, where local features $\{v, s\}$ are also projected as d -dimensional representations. In this work, f takes as input S3D [45] or CLIP [30] features from a fixed-length clip, and the inputs for g are from a sentence-based neural model that transforms a set of words into a single vector. Global contrastive loss \mathcal{L}_{Global} is used to ensure that the representations from each of the modalities at the global level are comparable. A second localized attention contrastive loss \mathcal{L}_{Local} encourages representations from finer granularity, e.g., spatial regions and words, to be close in the embedding space.

3.2. Representations guided frame sampling

Learning representations from multimodal self-supervision is challenging since the narration is very likely to be noisy, thus containing more information than the actual task descriptions. The relevant task will often not be present in all frames due to poor temporal alignment or cut scenes [14, 27], which is one of the key differences between weakly supervised vision-caption grounding and multimodal self-supervised grounding. Motivated by this setup, this work pursues a frame selection strategy to improve object grounding and temporal alignment during training. We start from a longer sequence U , where $U > T$, which includes the video frames before and after the ASR boundaries that might contain actions or objects in the sentence. Our goal is to find T frames out of the U frames that are most relevant to the actions and objects in the sentence \mathcal{S} . We formalize it as an optimal transport problem utilizing the Sinkhorn-Knopp algorithm [9].

Optimal transport for word-to-frame assignment. To acquire the optimal assignment from word features to video frames, an assignment matrix \mathbf{Q} is computed from each

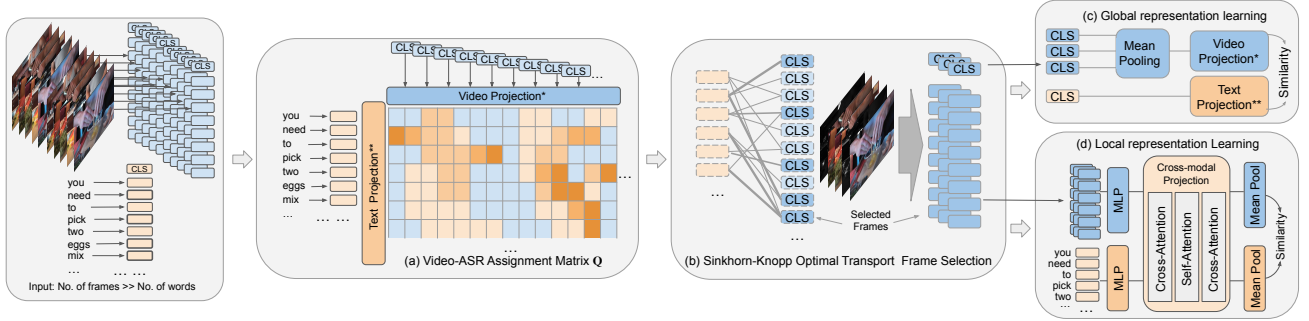


Figure 2: **Spatio-temporal grounding approach.** (a) We want to select frames with possible groundable objects and tasks. To this end, projected word features are matched with respective frame features. (b) Sinkhorn-knopp optimal transport is then leveraged to ensure the variety of our selected frames. (c) Based on the selected frames, a global representation is learned to allow for temporal localization as well as (d) a local representation to ground the action description to the spatial region.

video and ASR pair as shown in Figure 2(a). This cross-model optimal transport mechanism is applied to assignment \mathbf{Q} from the projected cross-model similarity \mathbf{P} between word tokens and each video frame, where $\mathbf{P} = g(\mathcal{S}) \otimes f(\mathcal{V})^\top \in \mathbb{R}^{K \times U}$. To compute the assignment matrix, the text and video projection layers from the global representation in Figure 2(c) are used to project multimodal features into a common space for feature similarity calculation. To ensure that the word-to-frame assignment contains more diversity instead of just saturated assignments to a single video frame, we add a constraint that requires label assignments to be equally distributed across various video frames representing diverse object/action concepts. This is achieved by restricting \mathbf{Q}_v to a *transportation polytope* \mathcal{Q}_v :

$$\mathcal{Q} = \{ \mathbf{Q} \in \mathbb{R}_+^{U \times K} \mid \mathbf{Q} \mathbf{1}_K = \frac{1}{U} \mathbf{1}_U, \mathbf{Q}^\top \mathbf{1}_U = \frac{1}{K} \mathbf{1}_K \}, \quad (1)$$

which enforces the soft-assignment distribution \mathbf{Q} to assign an equal marginal probability to each of the U frames instead of converging to a single frame. The vector $\mathbf{1}_U$ represents one vector with dimension $U \times 1$.

The next goal is to enforce this *transportation polytope* \mathcal{Q} . A solution for \mathbf{Q} is now computed using the optimal transport Sinkhorn-Knopp algorithm [6, 9] as shown in Figure 2 (b). The Sinkhorn-Knopp algorithm also normalizes the distribution of \mathbf{P} as:

$$\mathbf{Q} = \text{Diag}(\alpha) \exp\left(\frac{\mathbf{P}}{\varepsilon}\right) \text{Diag}(\beta), \quad (2)$$

where α and β are scaling vectors that restrict \mathbf{Q} to have a uniform distribution across region assignment. ε is a parameter that controls the smoothness of the mapping [6].

The T frames are then selected by the corresponding assignment \mathbf{Q} from the frames with top T aggregated similarity sum over each word for further training. Note that the selection part \mathbf{P} is from a trainable projection. While acquiring a better word-to-region projection during training, we hypothesize that the frame selection also benefits. The respective frame selection strategy is evaluated in Table 4.

3.3. Local representations for spatial localization

To capture multimodal interaction with finer granularity, we apply the widely used attention mechanism to learn the projection between tokenized features as shown in Figure 2(d). We extract spatio-temporal region features v_{tn} from the video. Also, we extract word features s_k which represents the feature from word k . All tokenized features are projected through a linear layer. To compute attention between the tokenized features, we stacked two cross-modal attention layers with a self-attention layer in the middle, as illustrated in Figure 2 (d). Cross-modal attention is computed similar to the standard attention mechanism [21]. Given a spatio-temporal token v_{tn} from a video, we compute the attention score to all of the words s_k , where $k \in \{1, \dots, K\}$ in the ASR sentence \mathcal{S} by $\alpha_{tnk} = \frac{\exp(e_{tnk})}{\sum_{k=1}^K \exp(e_{tnk})}$ in the same video clip, where $e_{tnk} = \text{cosine}(v_{tn}, s_k)$. We then acquire a contextual video token feature $\bar{v}_{tn} = \sum_{k=1}^K \alpha_{tnk} s_k$, which encoded text contextual information. Note that the contextual vector is represented by aggregating the representations from the other modality. Follow the standard self-attention computation [41] K, Q, V represent the features for the keys, queries, and values as:

$$\text{Attn}(K, Q, V) = \text{softmax}\left(\frac{(Q^\top K)}{\sqrt{d_k}}\right) V \quad (3)$$

where d_k is the dimension of the key. In our case, we feed each contextual features $\{\bar{v}_{tn}, \bar{s}_k\}$ right after the first cross-attention layer to be the K, Q, V to acquire its self-attended representation. The localized attention model was trained using contrastive loss. To represent the video clip \mathcal{V} and ASR sentence \mathcal{S} , we mean-pool over the spatio-temporal tokens in video $\bar{V} = \frac{1}{TN} \sum_{r=1}^{TN} \bar{v}_r$, and words $\bar{S} = \frac{1}{K} \sum_{k=1}^K \bar{s}_k$ respectively. Let $(\bar{V}^{(l)}, \bar{S}^{(l)})$ be the l -th training example pair. We adopt the Noise Contrastive Estimation (NCE) loss [13] and the localized attention losses

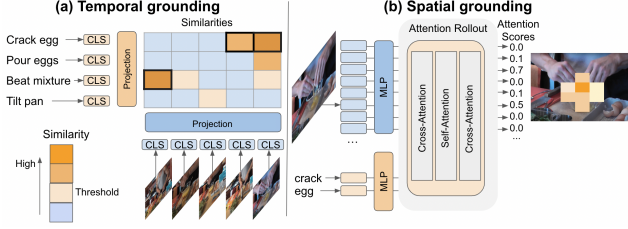


Figure 3: **Spatio-temporal inference.** Both temporal and spatial representations are used for spatio-temporal grounding: Starting by predicting the action boundary, spatial grounding is performed on the selected frames using the predicted label to find corresponding regions.

\mathcal{L}_{Local} :

$$-\frac{1}{B} \sum_{l=1}^B \left[\left(\log \frac{e^{\bar{V}_l \cdot \bar{S}_l - \delta}}{e^{\bar{V}_l \cdot S_l - \delta} + \sum_{\substack{k=1 \\ k \neq l}}^B e^{\bar{V}_k \cdot \bar{S}_l}} \right) + \left(\log \frac{e^{\bar{V}_l \cdot S_l - \delta}}{e^{\bar{V}_l \cdot S_l - \delta} + \sum_{\substack{k=1 \\ k \neq l}}^B e^{\bar{V}_l \cdot \bar{S}_k}} \right) \right] \quad (4)$$

where B stands for the batch. \bar{V}_k^{imp} and \bar{S}_k^{imp} represent imposter samples, and δ is a margin hyperparameter.

3.4. Learning multimodal global representations

We learn to project the global representation of a video clip and a sentence by contrastive loss, as shown in Figure 2(c). This loss pulls the representations of the two modalities from the same instance closer while pushing the imposter modality pairs sampled from different videos further away. We use the NCE loss function [13]. The global contrastive loss \mathcal{L}_{Global} follows the formulation as Equation 4 while using the global representations V and S , which is the [CLS] tokens from both modalities, instead of the local representations. Projecting the global features to the same space ensures that the features across different modalities are comparable. Since global representations encode information from the entire video, it is essential in encoding temporal information for the later downstream tasks. The final model is optimized by the sum of both losses.

3.5. Inference for spatio-temporal grounding.

To perform spatio-temporal grounding on untrimmed videos, we start from temporal action detection as shown in Figure 3. Given a pool of possible action descriptions on the left and an untrimmed video, we perform feature similarity matching using the global representation ([CLS] token) per frame with a threshold τ to filter backgrounds. We pick the action class with the largest similarity score per frame. Later, we use the predicted action class and feed it into the local representation branch to compute spatial grounding. We follow attention rollout [1] to compute feature similarity between visual tokens and text tokens through the cross-

attention and self-attention. In the end, we acquire an attention heatmap for later downstream evaluation.

4. GroundingYoutube Benchmark

Current downstream datasets either provide spatial [38, 34], temporal annotation [54, 20, 39], or short video clip with spatio-temporal annotation [49, 8]. These datasets do not provide the opportunity to evaluate both aspects, spatial and temporal grounding, in an untrimmed long video manner. We, therefore, extend one of the current benchmarks, MiningYoutube [20], which already provides dense temporal annotations, and we annotate video clips in the dataset with spatial information.

Annotating the spatio-temporal extent of actions can be challenging as there is no clear visible outline as in object annotation, nor is there a unique signal to indicate the temporal begin and end points. Similarly, grounding systems do not usually produce pixel-exact bounding boxes but rather indicate regions of interest. Detector-free spatial grounding models [5] address this fuzziness by relying on pointing game accuracy, thus only using the center point of the heatmap for evaluation. Lending on this idea, annotators were asked to mark the presumed center point of the action. Compared to bounding boxes, center point annotation can be advantageous because annotators are not visually distracted by object outlines, so it is more likely that the most important region will be selected. We capture five annotations per frame, resulting in a density-based heatmap.

Starting from 5,091 clips showing one of the 512 action classes, we adopt the methodology used for temporal action localization developed in [11] and label one frame per second, resulting in 26,987 frames. We annotated all frames with five repeats per image, resulting in 134,935 point labels in total. Each video contains an average of 10 actions. Following the previous evaluation setting using bounding boxes [18], we get the union of all annotated points in a single frame with an additional distance for constructing the bounding box. We provide more information on the annotation process is available in the supplementary.

5. Experiments

5.1. Datasets

Training Data: **HowTo100M dataset** contains 1.2M instructional videos along with their corresponding automatically generated speech (ASR) transcriptions. We randomly selected 200K video clips from the *Food and Entertaining* category for training.

Downstream Datasets: **GroundingYoutube (GYT)** is used to evaluate the task of multi-action spatio-temporal grounding as described in Section 4. **MiningYoutube (MYT)** [20] provides temporal annotation and is limited to the domain of cooking instruction videos. The dataset

Method	Backbone	DataSet	Supervision	Modality	GroundingYoutube						
					IoU+Point	mAP					
						0.1	0.2	0.3	0.4	0.5	0.1:0.5
CoMMA* [38]	S3D-word2vec	HT250K	Self	VT	1.02	2.18	1.72	1.11	0.93	0.37	1.26
MIL-NCE [27]	S3D-word2vec	HT100M	Self	VT	4.67	33.94	25.16	12.65	3.42	0.41	15.11
Ours	S3D-word2vec	HT200K	Self	VT	9.12	42.70	35.49	25.16	16.22	10.05	25.92
GLIP [22]	Swin-L	Cap24M	Weak	IT	1.24	2.83	2.10	1.52	0.96	0.37	1.56
CoMMA† [38]	CLIP	HT200M	Self	VT	1.68	3.51	2.32	1.88	0.99	0.40	1.82
CLIP [30]	CLIP	HT200K	Self	IT	3.59	29.54	22.15	9.16	2.48	0.39	12.74
RegionCLIP [51]	ResNet-101	CC3M	Weak	IT	5.65	35.65	27.43	15.69	4.31	0.86	16.78
Ours	CLIP	HT200K	Self	VT	10.09	42.81	36.05	25.84	17.10	11.35	26.63

Table 1: **Spatio-temporal grounding on GroundingYouTube full videos.** (V: video, I: image, T: text.)

features 250 full instructional videos, which are annotated with 512 action classes and temporal boundary information. We use it to evaluate the temporal grounding abilities. **YouCook-Interaction (YC-Inter)** [38] is an extension of the YouCook2 dataset [53] for cooking instruction, which provides bounding boxes for 6K selected frames. The bounding boxes usually comprise the hand and the tool mentioned in the respective sentence-wise annotation. We evaluate the spatial grounding abilities of models on this dataset. To further benchmark on general video domains with human-object interaction, we test spatial grounding on the **V-HICO** dataset [23] with 6.5k videos with human-object interaction bounding boxes annotations, as well as on the **Daly** action dataset [43], featuring videos consisting of daily actions such as “brushing teeth”.

5.2. Baseline methods

The proposed system is compared to various multimodal methods based on self- and weak supervision to evaluate the approach and related data annotation. Namely, we choose MIL-NCE [27] as the standard baseline for this task, which utilizes S3D[45] and word2vec[29] to project two modalities into a common space. We include CoMMA [38] as the best-performing model for spatial representations in self-supervised learning. We noted as CoMMA* to represent the model uses weights shared by the author². CLIP [30] is an image-text model trained with transformer architecture on image caption pairs which shows great results on multimodal video tasks [26]. We further apply CLIP as the backbone and train with [38] to construct CoMMA†. GLIP[22] and RegionCLIP [51] are state-of-the-art image-text grounding models to combine the large-scale image caption pretraining and object detection fine-tuning. Such supervision is considered weak supervision since the bounding box proposal network was trained on other human-annotated data. We also include two fully supervised models, TubeDETR [46] and STCAT [17] trained on Vid-STG dataset [49] with 448 resolution for compari-

²We thank the authors for providing code and weights.

son. The two models utilize human-annotated referring expression sentences and corresponding bounding boxes during training. For the models using S3D[45] visual backbones, we use the pre-trained weights from MIL-NCE [27] for initialization. For the models using word2vec features, we follow [27] to use the max-pooled word embedding to represent the sentence (global representation) since there is no [CLS] token. Also, the sentence feature is used for the query word selection instead of the [CLS] token. We used the mean-pooled S3D spatio-temporal features to represent the global representation of the video following the S3D architecture [45]. For CLIP[30] backbones, we use the pre-trained transformer ViT-B/32. More implementation details and experimental settings are in the supplementary.

5.3. Downstream Tasks

We considered the following downstream tasks to evaluate spatio-temporal grounding abilities of various models:

(i) **Spatio-temporal grounding in untrimmed video** is evaluated on our annotated GroundingYoutube dataset. We combined the spatial and temporal grounding evaluation as before [20, 2] to form the spatio-temporal evaluation. The entire video and the respective pool of action instructions were provided. The model needs to localize each action step in temporal (start-time/end-time) and spatial (location in the video) as described in Figure 3. We evaluate in two metrics: **IoU+Pointing game** combines the evaluation setting from the spatial grounding [2] and temporal grounding [20] metrics. For each video frame, the prediction is correct when the model predicts the correct action for the frame. Also, given the predicted action as a query, the maximum point of the heatmap aims to lie within the desired bounding box. We then compute the Intersection over Union (IoU) over all the predictions with the GT to acquire the final score. We also compute **video mAP** following previous evaluation [11], where we set IoU threshold between GT and predicted spatio-temporal tubes. A prediction is correct when it surpasses the IoU threshold. We then compute the mAP over all classes. We form a 3D prediction mask following Figure

Method	Backbone	Data	Super.	Mod.	YouCook-Inter	GroundingYoutube		V-HICO		Daly	
					Acc	Acc	mAP	Acc	mAP	Acc	mAP
MIL-NCE [27]	S3D	HT100M	Self	VT	23.67	27.45	8.21	12.65	11.23	13.84	24.23
CoMMA* [38]	S3D	HT250K	Self	VT	48.63	47.68	23.38	40.97	21.45	54.48	33.39
Ours	S3D	HT200K	Self	VT	53.98	60.62	44.93	44.32	24.31	66.35	45.93
CLIP [30]	CLIP	HT200K	Self	IT	14.10	12.50	3.49	29.23	12.51	18.02	27.28
CoMMA† [38]	CLIP	HT200K	Self	VT	52.65	47.56	36.42	55.20	34.54	61.06	44.37
RegionCLIP [51]	RN50x4	CC3M	Weak	IT	51.56	52.84	23.42	57.92	37.82	67.12	48.62
GLIP [22]	Swin-L	Cap24M	Weak	IT	52.84	53.62	24.73	66.05	41.17	-	-
Ours	CLIP	HT200K	Self	VT	57.10	55.49	43.12	60.71	39.28	70.08	50.56
TubeDETR [46]	MDETR	Vid-STG	Full	VT	51.63	53.24	41.76	63.23	40.87	84.21	62.98
STCAT [17]	ResNet-101	Vid-STG	Full	VT	54.47	55.90	44.21	65.34	41.10	85.42	63.94

Table 2: **Video spatial grounding.** We evaluate using pointing game accuracy and mean average precision.

Method	Backbone	Data	Super.	IoU	IoD
Mining: MLP [27]	TSM	MiningYT	Weak	9.80	19.20
CoMMA* [38]	S3D-word2vec	HT250K	Self	2.05	5.63
MIL-NCE [27]	S3D-word2vec	HT100M	Self	18.69	26.74
Ours	S3D-word2vec	HT200K	Self	19.18	27.65
Ours	CLIP	HT200K	Self	19.88	28.50

Table 3: **Temporal Grounding on MiningYoutube.**

3 and compute IoU between our 3D heatmap and 3D tube.

(ii) **Spatial grounding** is given a text query description to localize the corresponding region in the trimmed video. We use GroundingYoutube, Youcook-Interaction, V-HICO, and Daly for evaluation. This task is evaluated using the **pointing game accuracy**. Given the query text and video, we compute the attention heatmap on the video as described in Figure 3(b). If the highest attention similarity score lies in the ground truth bounding box, the result counts as a “hit” and counts as “miss” otherwise. The final accuracy is calculated as a ratio between hits to the total number of predictions $\frac{\# \text{ hits}}{\# \text{ hits} + \# \text{ misses}}$. We report the mean average precision (**mAP**) following the settings from V-HICO [23]. Given a human-object category as the text query, we aim to localize the spatial location in the video frame. The predicted location is correct if their Intersection over-Union (IoU) with ground truth bounding boxes is larger than 0.3. Since we do not use any bounding box proposal tools or supervision, we create an attention heatmap as described in Figure 3(b) to create a mask for IoU computation. We follow [23] and compute the mAP over all verb-object classes.

(iii) **Temporal grounding** provides videos with the respective actions and their ordering, including the background. The goal is to find the correct frame-wise segmentation of the video. We follow the inference procedure in [20] to compute the alignment given our similarity input matrix. The task is evaluated by intersection over detection (IoD), defined as $\frac{G \cap D}{D}$ the ratio between the intersection of ground-truth action G and prediction D to prediction D , and the Jaccard index, which is an (IoU) given as $\frac{G \cap D}{G \cup D}$.

5.4. Comparison with state-of-the-art methods

(i) **Spatio-temporal grounding in untrimmed video:** We first compare the proposed method to other approaches designed for either spatial or temporal grounding in Table 1. It shows that the proposed method improves over the other baselines demonstrating the model’s ability to incorporate global (temporal) and local (spatial) representations. Further, models without specific loss designs for spatial grounding (MIL-NCE[27], CLIP[30]) show good mAP scores but lower pointing game accuracy. Out of the two weakly supervised methods, GLIP[22] and RegionCLIP[51]), trained with aligned image-text, RegionCLIP show significantly better performance in this setting, while both perform in a similar range in the spatial grounding scenario (see Table 2) with GLIP even outperforming RegionCLIP on the V-HICO dataset. We attribute this behavior to the fact that RegionCLIP is rather able to distinguish frames with relevant queries from background frames than GLIP, leading to better temporal localization. Note that supervised spatio-temporal grounding approaches [46, 17] are not directly applicable in this evaluation since such methods assume the given text query to be ground-truth. The model must distinguish the correct text query from a pool of action lists. We include an evaluation setting in the supplement where the GT-text queries were provided.

(ii) **Spatial grounding:** Second, we compare the performance of the proposed framework to other methods on the task of spatial grounding, including models with weak supervision, as well as models trained in a fully supervised setting. In the instruction video domain (GYT, YC-Inter), the proposed approach achieves the best result among all weakly and self-supervised trained methods. In the general domain, such as V-HICO and Daly, the method also achieves competitive results, showing the generalizability of the model to other domains. We attribute this to the transformer architecture in the text branch inheriting knowledge from the open domain during large-scale training, while in contrast the model’s performance using word2vec

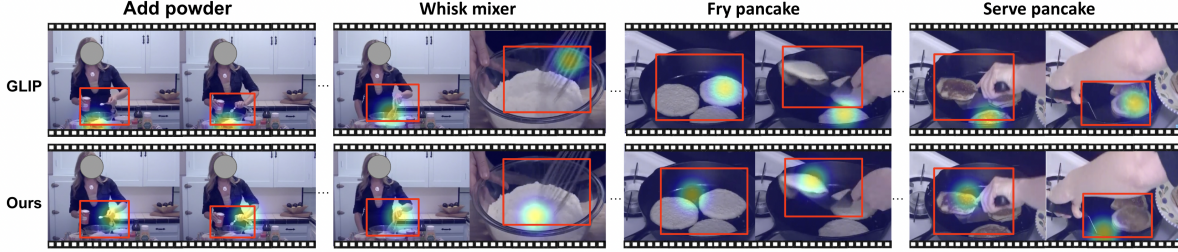


Figure 4: **Visualization on GroundingYoutube dataset.** Red box: annotation. Heatmap: prediction from the model.

	GroundingYT Spatio-temporal	MiningYT Temporal	YouCook-Inter. Spatial
None	15.1	17.8	55.5
Global selection	15.7	18.5	54.3
Local selection	15.6	18.1	56.3
Sinkhorn	17.1	19.9	57.1
only Local loss	5.7	4.5	54.3
only Global loss	7.6	18.8	32.5
w/ Both loss	17.1	19.9	57.1
Self+Cross	15.4	18.7	54.1
Cross+Self	15.9	18.9	54.5
Cross+Cross	16.5	19.3	56.2
Cross+Self+Cross	17.1	19.9	57.1

Table 4: **Ablations for training:** (a) Sinkhorn strategy results in better supervision. (b) both losses contribute to the final loss, and the existence of global loss helps the localization task. (c) combining cross and self-attention layers boosts the local representation learning performance.

dropped in these datasets. Note that in the Daly dataset, the classes are verbs, which are not detectable by the object-focused model GLIP. Compared to their weakly trained counterparts, fully-supervised model (TubeDETER [46], STCAT[17]) achieve decent performance in the general domain (V-HICO, Daly) and slightly lower performance in instruction domain (GYT, YC-Inter) due to the domain gap with respect to the training data.

(iii) **Temporal grounding:** We finally compare the task of temporal grounding in Table 3. It shows that global representations also profit from local representation learning, achieving state-of-the-art results in temporally localizing actions in untrimmed videos. This hypothesis is further validated in the ablation studies in Table 4, where we ablate both losses for all three settings and show a consistent improvement in the joint loss formulation.

5.5. Ablation study

We perform ablation studies with respect to all three settings, spatio-temporal grounding as well as spatial and temporal grounding alone, reporting performance for spatio-temporal grounding on GroundingYT using mAP with IoU@0.4, on temporal grounding using MiningYT IoU, and

on spatial grounding using YouCook-Inter. pointing game.

Frame selection strategy. We perform an ablation on the frame selection strategies in Figure 2(b). In Table 4, *None* uses the ASR boundary ($U = T$) as our video training data. *Global* utilizes the global sentence feature [CLS] token as the query to rank the top T similar frames as the selected frames for training. *Local* uses the words instead of the sentence as a query and selects the frames with the closest feature distance. We have shown that selecting frames based on sinkhorn leads to more variety of visual concepts but also captures frames with possible groundable objects.

Global and local loss. As mentioned in the spatio-temporal evaluation, both features contribute significantly to the final grounding result. We test the model by ablating out each loss. As shown in Table 4, not only that each loss contributes to the task of spatio-temporal grounding on the GYT, but also the whole is more than the sum of its parts (losses) since this task requires both spatial and temporal detection. The reduced impact of the global loss in the case of YC-Inter is based on the fact that this is a pure spatial grounding dataset (no background frames) without temporal detection, and the local loss plays a more critical role. We observe the same patterns in the temporal grounding result for MYT, where spatial localization wasn't directly contributing to the final performance.

Attention architecture. We tested different architectures by stacking the self-attention or cross-attention block in the model for computing contextualized local representations as shown in Figure 2(d). As shown in Table 4, we found the standard multimodal transformer architecture (self+cross) to have the worst performance. Using two cross-attention blocks was beneficial in incorporating more cross-modal interaction between local features. Finally, including a self-attention layer slightly improves the final representations by encoding better single-modality representations.

5.6. Qualitative results

We visualize our spatio-temporal result in Figure 4. For the GLIP model, we output the bounding box with the highest confidence score and visualize its center point. We found GLIP model focuses on the salient object while our model focuses more on human-object interaction.

6. Conclusion

We presented an approach for learning spatio-temporal grounding with self-supervision and a new dataset: GroundingYoutube annotations. Our method includes a frame selection mechanism that identifies frames with groundable objects to adapt the learning process for untrimmed videos. Furthermore, we jointly learn global representations, which capture temporal information, and local representations learning fine-grained multimodal interactions between video and text. We conducted extensive experiments to evaluate the performance of our approach showing state-of-the-art performance in spatio-temporal grounding, as well as temporal and spatial grounding alone.

References

- [1] Samira Abnar and Willem Zuidema. Quantifying attention flow in transformers. *arXiv preprint arXiv:2005.00928*, 2020. 5
- [2] Hassan Akbari, Svebor Karaman, Surabhi Bhargava, Brian Chen, Carl Vondrick, and Shih-Fu Chang. Multi-level multimodal common semantic space for image-phrase grounding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12476–12486, 2019. 2, 6
- [3] Hassan Akbari, Liangzhe Yuan, Rui Qian, Wei-Hong Chuang, Shih-Fu Chang, Yin Cui, and Boqing Gong. Vatt: Transformers for multimodal self-supervised learning from raw video, audio and text. *Advances in Neural Information Processing Systems*, 34, 2021. 1, 3
- [4] Jean-Baptiste Alayrac, Adria Recasens, Rosalia Schneider, Relja Arandjelović, Jason Ramapuram, Jeffrey De Fauw, Lucas Smaira, Sander Dieleman, and Andrew Zisserman. Self-supervised multimodal versatile networks. *Advances in Neural Information Processing Systems*, 33:25–37, 2020. 1, 3
- [5] Assaf Arbelle, Sivan Doveh, Amit Alfassy, Joseph Shtok, Guy Lev, Eli Schwartz, Hilde Kuehne, Hila Barak Levi, Prasanna Sattigeri, Rameswar Panda, et al. Detector-free weakly supervised grounding by separation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1801–1812, 2021. 5
- [6] Mathilde Caron, Ishan Misra, Julien Mairal, Priya Goyal, Piotr Bojanowski, and Armand Joulin. Unsupervised learning of visual features by contrasting cluster assignments. *Advances in Neural Information Processing Systems*, 33:9912–9924, 2020. 4
- [7] Brian Chen, Andrew Rouditchenko, Kevin Duarte, Hilde Kuehne, Samuel Thomas, Angie Boggust, Rameswar Panda, Brian Kingsbury, Rogerio Feris, David Harwath, et al. Multimodal clustering networks for self-supervised learning from unlabeled videos. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 8012–8021, 2021. 1, 3
- [8] Zhenfang Chen, Lin Ma, Wenhan Luo, and Kwan-Yee Kenneth Wong. Weakly-supervised spatio-temporally grounding natural sentence in video. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 1884–1894, Florence, Italy, July 2019. Association for Computational Linguistics. 2, 5
- [9] Marco Cuturi. Sinkhorn distances: Lightspeed computation of optimal transport. 2013. 2, 3, 4
- [10] Andrea Frome, Greg S Corrado, Jon Shlens, Samy Bengio, Jeff Dean, Marc’Aurelio Ranzato, and Tomas Mikolov. Devise: A deep visual-semantic embedding model. *Advances in neural information processing systems*, 26, 2013. 2
- [11] Chunhui Gu, Chen Sun, David A Ross, Carl Vondrick, Caroline Pantofaru, Yeqing Li, Sudheendra Vijayanarasimhan, George Toderici, Susanna Ricco, Rahul Sukthankar, et al. Ava: A video dataset of spatio-temporally localized atomic visual actions. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 6047–6056, 2018. 5, 6
- [12] Agrim Gupta, Piotr Dollar, and Ross Girshick. Lvis: A dataset for large vocabulary instance segmentation. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 5356–5364, 2019. 3
- [13] Michael Gutmann and Aapo Hyvärinen. Noise-contrastive estimation: A new estimation principle for unnormalized statistical models. In *AISTATS*, 2010. 4, 5
- [14] Tengda Han, Weidi Xie, and Andrew Zisserman. Temporal alignment networks for long-term video. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 2906–2916, 2022. 2, 3
- [15] FC Heilbron, V Escorcia, B Ghanem, and J Niebles. A large-scale video benchmark for human activity understanding. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, 2015*. 961, volume 970, 2019. 3
- [16] Yu-Gang Jiang, Jingen Liu, A Roshan Zamir, George Toderici, Ivan Laptev, Mubarak Shah, and Rahul Sukthankar. Thumos challenge: Action recognition with a large number of classes. <http://crcv.ucf.edu/THUMOS14/>, 2014. 3
- [17] Yang Jin, yongzhi li, Zehuan Yuan, and Yadong MU. Embracing consistency: A one-stage approach for spatio-temporal video grounding. In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho, editors, *Advances in Neural Information Processing Systems*, 2022. 1, 2, 6, 7, 8
- [18] Vicky Kalogeiton, Philippe Weinzaepfel, Vittorio Ferrari, and Cordelia Schmid. Action tubelet detector for spatio-temporal action localization. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 4405–4413, 2017. 5
- [19] Aishwarya Kamath, Mannat Singh, Yann LeCun, Gabriel Synnaeve, Ishan Misra, and Nicolas Carion. Mdetri-modulated detection for end-to-end multi-modal understanding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1780–1790, 2021. 2
- [20] Hilde Kuehne, Ahsan Iqbal, Alexander Richard, and Juergen Gall. Mining youtube-a dataset for learning fine-grained action concepts from webly supervised video data. 2019. 1, 2, 3, 5, 6, 7
- [21] Kuang-Huei Lee, Xi Chen, Gang Hua, Houdong Hu, and Xiaodong He. Stacked cross attention for image-text matching.

- In *Proceedings of the European conference on computer vision (ECCV)*, pages 201–216, 2018. 4
- [22] Liunian Harold Li, Pengchuan Zhang, Haotian Zhang, Jianwei Yang, Chunyuan Li, Yiwu Zhong, Lijuan Wang, Lu Yuan, Lei Zhang, Jenq-Neng Hwang, et al. Grounded language-image pre-training. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10965–10975, 2022. 2, 3, 6, 7
- [23] Shuang Li, Yilun Du, Antonio Torralba, Josef Sivic, and Bryan Russell. Weakly supervised human-object interaction detection in video via contrastive spatiotemporal regions. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1845–1855, 2021. 6, 7
- [24] Yikang Li, Jenhao Hsiao, and Chiuman Ho. Videoclip: A cross-attention model for fast video-text retrieval task with image clip. In *Proceedings of the 2022 International Conference on Multimedia Retrieval*, pages 29–33, 2022. 3
- [25] Tsung-Yi Lin, Michael Maire, Serge Belongie, James Hays, Pietro Perona, Deva Ramanan, Piotr Dollár, and C Lawrence Zitnick. Microsoft coco: Common objects in context. In *Computer Vision—ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6–12, 2014, Proceedings, Part V 13*, pages 740–755. Springer, 2014. 3
- [26] Huaishao Luo, Lei Ji, Ming Zhong, Yang Chen, Wen Lei, Nan Duan, and Tianrui Li. Clip4clip: An empirical study of clip for end to end video clip retrieval and captioning. *Neurocomputing*, 508:293–304, 2022. 6
- [27] Antoine Miech, Jean-Baptiste Alayrac, Lucas Smaira, Ivan Laptev, Josef Sivic, and Andrew Zisserman. End-to-end learning of visual representations from uncurated instructional videos. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9879–9889, 2020. 1, 2, 3, 6, 7
- [28] Antoine Miech, Dimitri Zhukov, Jean-Baptiste Alayrac, Makarand Tapaswi, Ivan Laptev, and Josef Sivic. Howto100m: Learning a text-video embedding by watching hundred million narrated video clips. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2630–2640, 2019. 1, 2, 3
- [29] Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. Efficient estimation of word representations in vector space. In *arXiv preprint arXiv:1301.3781*, 2013. 6
- [30] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International Conference on Machine Learning*, pages 8748–8763. PMLR, 2021. 3, 6, 7
- [31] Michaela Regneri, Marcus Rohrbach, Dominikus Wetzels, Stefan Thater, Bernt Schiele, and Manfred Pinkal. Grounding action descriptions in videos. *Transactions of the Association for Computational Linguistics*, 1:25–36, 2013. 3
- [32] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems*, 28, 2015. 2
- [33] Andrew Rouditchenko, Angie Boggust, David Harwath, Brian Chen, Dhiraj Joshi, Samuel Thomas, Kartik Adhikari, Hilde Kuehne, Rameswar Panda, Rogerio Feris, et al. Avlnet: Learning audio-visual language representations from instructional videos. *arXiv preprint arXiv:2006.09199*, 2020. 3
- [34] Jing Shi, Jia Xu, Boqing Gong, and Chenliang Xu. Not all frames are equal: Weakly-supervised video grounding with contextual similarity and visual clustering losses. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10444–10452, 2019. 2, 3, 5
- [35] Nina Shvetsova, Brian Chen, Andrew Rouditchenko, Samuel Thomas, Brian Kingsbury, Rogerio Feris, David Harwath, James Glass, and Hilde Kuehne. Everything at once—multimodal fusion transformer for video retrieval. In *CVPR*, 2022. 1, 3
- [36] Mattia Soldan, Alejandro Pardo, Juan León Alcázar, Fabian Caba Heilbron, Chen Zhao, Silvio Giancola, and Bernard Ghanem. Mad: A scalable dataset for language grounding in videos from movie audio descriptions. *arXiv preprint arXiv:2112.00431*, 2021. 3
- [37] Rui Su, Qian Yu, and Dong Xu. Stvgbert: A visual-linguistic transformer based framework for spatio-temporal video grounding. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1533–1542, 2021. 2
- [38] Reuben Tan, Bryan Plummer, Kate Saenko, Hailin Jin, and Bryan Russell. Look at what i’m doing: Self-supervised spatial grounding of narrations in instructional videos. *Advances in Neural Information Processing Systems*, 34, 2021. 2, 3, 5, 6, 7
- [39] Yansong Tang, Dajun Ding, Yongming Rao, Yu Zheng, Danyang Zhang, Lili Zhao, Jiwen Lu, and Jie Zhou. Coin: A large-scale dataset for comprehensive instructional video analysis. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1207–1216, 2019. 1, 5
- [40] Zongheng Tang, Yue Liao, Si Liu, Guanbin Li, Xiaojie Jin, Hongxu Jiang, Qian Yu, and Dong Xu. Human-centric spatio-temporal video grounding with visual transformers. *IEEE Transactions on Circuits and Systems for Video Technology*, 2021. 2
- [41] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017. 4
- [42] Zhaoqing Wang, Yu Lu, Qiang Li, Xunqiang Tao, Yandong Guo, Mingming Gong, and Tongliang Liu. Cris: Clip-driven referring image segmentation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 11686–11695, 2022. 2
- [43] Philippe Weinzaepfel, Xavier Martin, and Cordelia Schmid. Human action localization with sparse spatial supervision. *arXiv preprint arXiv:1605.05197*, 2016. 6
- [44] Jason Weston, Samy Bengio, and Nicolas Usunier. Wsabie: Scaling up to large vocabulary image annotation. In *Twenty-Second International Joint Conference on Artificial Intelligence*, 2011. 2
- [45] Saining Xie, Chen Sun, Jonathan Huang, Zhuowen Tu, and Kevin Murphy. Rethinking spatiotemporal feature learn-

- ing: Speed-accuracy trade-offs in video classification. In *Proceedings of the European conference on computer vision (ECCV)*, pages 305–321, 2018. 3, 6
- [46] Antoine Yang, Antoine Miech, Josef Sivic, Ivan Laptev, and Cordelia Schmid. Tubedetr: Spatio-temporal video grounding with transformers. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16442–16453, 2022. 1, 2, 6, 7, 8
- [47] Zhengyuan Yang, Zhe Gan, Jianfeng Wang, Xiaowei Hu, Faisal Ahmed, Zicheng Liu, Yumao Lu, and Lijuan Wang. Unitab: Unifying text and box outputs for grounded vision-language modeling. In *European Conference on Computer Vision*, pages 521–539. Springer, 2022. 2
- [48] Runhao Zeng, Haoming Xu, Wenbing Huang, Peihao Chen, Mingkui Tan, and Chuang Gan. Dense regression network for video grounding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10287–10296, 2020. 3
- [49] Zhu Zhang, Zhou Zhao, Yang Zhao, Qi Wang, Huasheng Liu, and Lianli Gao. Where does it exist: Spatio-temporal video grounding for multi-form sentences. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10668–10677, 2020. 2, 5, 6
- [50] Yang Zhao, Zhou Zhao, Zhu Zhang, and Zhijie Lin. Cascaded prediction network via segment tree for temporal video grounding. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 4197–4206, 2021. 3
- [51] Yiwu Zhong, Jianwei Yang, Pengchuan Zhang, Chunyuan Li, Noel Codella, Liunian Harold Li, Luwei Zhou, Xiyang Dai, Lu Yuan, Yin Li, et al. Regionclip: Region-based language-image pretraining. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 16793–16803, 2022. 2, 3, 6, 7
- [52] Luwei Zhou, Nathan Louis, and Jason J Corso. Weakly-supervised video object grounding from text by loss weighting and object interaction. In *British Machine Vision Conference*, 2018. 2, 3
- [53] Luwei Zhou, Chenliang Xu, and Jason J Corso. Towards automatic learning of procedures from web instructional videos. In *Thirty-Second AAAI Conference on Artificial Intelligence*, 2018. 3, 6
- [54] Dimitri Zhukov, Jean-Baptiste Alayrac, Ramazan Gokberk Cinbis, David Fouhey, Ivan Laptev, and Josef Sivic. Cross-task weakly supervised learning from instructional videos. 2019. 1, 3, 5