**LOCFORMER: Enabling Transformers to Perform Temporal Moment Localization on Long Untrimmed Videos With a Feature Sampling Approach**

Cristian Rodriguez-Opazo Electronics and Computer Science Edson Marrese-Taylor Electronics and Computer Science Basura Fernando Electronics and Computer Science
Hiroya Takamura National Institute of Advanced Industrial Science and Technology (AIST)
Qi Wu A*STAR Singapore

cristian.rodriguezopazo@adelaide.edu.au

University of Adelaide, Australian Institute for Machine Learning
National Institute of Advanced Industrial Science and Technology (AIST)
The University of Tokyo A*STAR Singapore

**Abstract**

We propose LOCFORMER, a Transformer-based model for video grounding which operates at a constant memory footprint regardless of the video length, i.e., number of frames. LOCFORMER is designed for tasks where it is necessary to process the entire long video and at its core lie two main contributions. First, our model incorporates a new sampling technique that splits the input feature sequence into a fixed number of sections and selects a single feature per section using a stochastic approach, which allows us to obtain a feature sample-set that is representative of the video content for the task at hand while keeping the memory footprint constant. Second, we propose a modular design that separates functionality, enabling us to learn an inductive bias via supervising the self-attention heads, while also effectively leveraging pre-trained text and video encoders. We test our proposals on relevant benchmark datasets for video grounding, showing that not only LOCFORMER can achieve excellent results including state-of-the-art performance on YouCookII, but also that our sampling technique is more effective than competing counterparts and that it consistently improves the performance of prior work, by up to 3.13% in the mean temporal IoU, ultimately leading to a new state-of-the-art performance on Charades-STA.

**1. Introduction**

Vision-and-language understanding is an important problem which has largely attracted the attention from both the computer vision (CV) and natural language processing (NLP) communities. Among tasks in this area, the temporal localization of moments remains a fundamental and challenging one. This task aims to identify the start and end time of a moment of interest in an input untrimmed video given the query in natural language [8,13,16,30,36,50]. Recent approaches have aimed at directly predicting the starting and ending temporal locations, or regressing them from the input video [18,38,53]. Although these models are more efficient than previous propose-and-rank-based approaches, they still require a considerable amount of computation and/or memory since they need to process the whole input video at once.

Recent improvements in both NLP and CV tasks can be attributed to the Transformer [43] model. Despite their success, one main drawback of these models is their compu-
tational cost, being a greatly limiting factor for many, with memory usage ballooning as model sizes increase to attain better performance. This issue has had a significant impact on the NLP community, recently leading to the proposal of several model variations to better deal with longer inputs such as documents [2, 25, 47] by using restricted, simplified or memory-efficient versions of the attention component. The advent of new, deeper Transformer-based models for image and video understanding suggests that these problems are likely to become more relevant in the CV community as well. This is exemplified by many existing developments in Transformer models for video understanding only being capable of processing short inputs at a time due to memory constraints. For example, TimeSformer-large [3] can only process inputs that are 24 seconds long\(^2\), ViViT [1] and X-ViT [4] can receive inputs that are up to 32 frames long, while other approaches like MERLOT [54] and ClipBERT [28] specifically sample a single or a few frames from the whole input video. Recent Transformer-based models for video grounding have taken a different approach, instead choosing to aggregate the video features during pre-processing with pooling techniques [58] in order to be able to handle longer inputs. Furthermore, many of the aforementioned approaches rely on the split-and-aggregate approach when processing long videos, where inputs are divided into sections which are processed separately by the model. Though many of the downstream tasks considered by these models do not specifically require temporal reasoning over the input videos, their applicability to tasks requiring temporal reasoning is limited, as it keeps models from capturing interactions across segments.

In light of this, we present LOCFORMER, a Transformer-based model for the task of temporal moment localization which operates at a constant memory footprint regardless of the input length, as shown in Figure 1. The success of the LOCFORMER relies on two key ideas. Firstly, LOCFORMER incorporates Stochastic Bucket-wise Feature Sampling (SBFS), which splits the sequence of input video feature into a fixed number of buckets and selects a single feature per bucket per iteration using a stochastic approach during training. While bucketing enables us to keep the memory budget limited by effectively shortening the input sequence length to the number of buckets, the stochastic nature of our approach allows us to obtain a better coverage of the video with sufficient stochasticity, obtaining a feature sample-set that is representative of the video content for the task at hand. This allows us to attain better generalization than traditional sampling methods like video-level down-sampling, i.e. extracting frames at low frame-rate and feature-level pooling.

Secondly, we propose a modular design that separates the functionality inside the model, enabling us to learn an inductive bias via supervising the behavior of some self-attention heads, but without interfering with the functionality of the heads of existing pre-trained models such as BERT [12], which we also incorporate into the model. Finally, we introduce a new loss to induce the correct temporal order of the predicted starting and ending locations of the target moment.

To demonstrate the effectiveness of our proposals, we conduct experiments on three challenging datasets, Charades-STA [15], ActivityNet Captions [5, 27] and YouCookII [61, 62]. We show that LOCFORMER is able to obtain state-of-the-art performance in the latter, and competitive results elsewhere. Moreover, we also show how SBFS can be easily combined with prior work, improving their performance in all datasets, leading to a new state-of-the-art on Charades-STA. We believe our results highlight the importance of sampling techniques as a valid mechanism to obtain better coverage of long input videos while keeping memory usage under budget. This ultimately provides a concrete direction for further research on tasks where it is necessary to cover long untrimmed videos, which include but are not limited to video grounding.

2. Related Work

Temporal Action and Moment Localization. The goal of Temporal Action localization is to solve the problem of recognizing and determining temporal boundaries of action instances in videos, with extensive previous work devoted to it [19, 20, 40]. Given the limitations of temporal action localization, which is restricted to a pre-defined list of labels, the task of language-driven temporal moment localization was introduced as a generalization [15, 22]. In this task, the goal is to determine the start and end times of the video segment that best corresponds to a given natural language query. As this requires the model to extract useful information from the textual semantics in the query in order to identify the moment, this task is also usually regarded as video grounding. Early approaches that tackled temporal moment localization, including the work of Liu et al. [32] and Ge et al. [17], were mainly based on the generation of proposals or candidate clips which could later be ranked. Soon after, Chen et al. [9], Chen and Jiang [10], and Xu et al. [50] focused mainly on reducing the number of proposals by producing query-guided or query-dependent approaches. Recently, Zhang et al. [58] also adopted a Transformer-based model for this setting, being the most relevant to our work.

The extensive computation of enumerating candidates in the above mentioned proposal-based methods led to the development of methods that can directly output the temporal coordinates of the segment, namely, proposal-free approaches. In this context, Ghosh et al. [18] first focused directly on predicting the start and end frames using regressions, and soon after Rodriguez-Opazo et al. [38] im-
proved results by modelling label uncertainty. While Mun et al. [34] and Zeng et al. [55] later proposed more sophisticated modality matching strategies, some more recent approaches have focused on better contextualizing I3D [6] video features by proposing other model variations [29]. More recently, Liu et al. [31], CPNet [29], VSLNet [57] have pushed performance further up. Finally, models like DORi, which also incorporates spatial features, [37] and CPN [59] have proposed ad-hoc graph-based approaches, with excellent results. Our contributions are orthogonal to these models, but also complementary because of their large memory consumption, as we will show in §4.5.

**Sampling.** To the best of our knowledge, the earliest example of a sampling technique that is similar to ours is the work of Nakagawa et al. [35], who proposed a stochastic version of dynamic time warping for speech recognition of the Japanese language in the late 80s. This idea was further extended by Chendra et al. [42] in the context of motion recognition, where a randomized version of dynamic time warping for this task was introduced. We also find several models that utilize sampling techniques for action recognition in videos, in this case to specifically select salient clips, such as SCSampler [26] and MGSampler [60], which were later adopted by models like MVFNet [48]. Also, Adaframe [49] recently proposed a framework that adaptively selects relevant frames on a per-input basis for fast video recognition.

**Transformers.** Finally, our work is also related to Transformer models proposed in the context of video-and-language understanding, and natural language processing. While most existing work is concerned with the pre-training of models on large datasets using general-purpose tasks such as masked-language modelling [11, 33], our approach in this paper is more specific and directly trains the model for the task at hand.

3. Proposed Approach

3.1. Overview

We assume that a given video $V \in \mathcal{V}$ can be characterized as a sequence of frames such that $V = \{v_t\}$ with $t = 1, \ldots, l$. Each video in $\mathcal{V}$ is annotated with a natural language passage $S \in \mathcal{S}$ where $S$ is a sequence of tokens $S = \{s_j\}$ with $j = 1, \ldots, m$, which describes what is happening in a certain period of time. Formally, this interval is defined by $t^s$ and $t^e$, the starting and ending points of the annotations in time, respectively. Although in the data a given video may be annotated with more than one single moment, and one natural language description may be associated to multiple moments, in this work we assume each derived case as an independent, separate training example.

Our model is trained to predict the most likely temporal localization of the contents of a given input query $S$ in terms of its start and end positions $t^s$ and $t^e$ in the video. We apply the mapping $\tau = (t \cdot n \cdot \text{fps})/l$ to transform frame/feature index to time, converting $t^s$ and $t^e$ into $\tau^s$ and $\tau^e$, which correspond to specific integer feature positions such that $\tau^s, \tau^e \in [1, \ldots, n]$.

**LOCFormer** follows the Transformer architecture [44], which has been recently extended to multi-modal scenarios as in UNITER [11] in the context of vision-and-language, and Recurrent VLN-BERT [23] for vision-and-language navigation. Our model operates on a sequences of tokens $\{s_j\}$ and a video $\{v_t\}$ characterized as a sequence of frames, as specified earlier. The overall architecture is composed by three main modules: (1) The Video Encoding Module, which is in charge of mapping video frames to vectors, and obtaining a sample that is representative of the video contents, (2) the Text Encoding Module, a Transformer model with dimension $d_m$ in charge of extracting useful representations from the natural language query, and
(3) the Localization Module, a multi-modal Transformer, also with hidden dimension $d_m$, which receives both textual and video features from the previous modules and is in charge of estimating $\tau^s$ and $\tau^e$. In the following subsections, we give details about each component and how they interact.

### 3.2. Video Encoding Module with Feature Sampling

Our video encoding module is in charge of mapping the $l$ input video frames into a sequence of video features $G = \{g_i \in \mathbb{R}^{d_v}, i = 1, \ldots, n\}$, and selecting a subset of these features that is representative of the contents of the video, which will later be fed into the localization module.

We assume input video features $G$ are extracted by a video encoding function $F_V(\cdot)$ and propose to limit the overall memory budget of the model by shortening the sequence of video features fed into the localization module. We do this in practice by proposing a technique that we call Stochastic Bucket-wise Feature Sampling (SBFS), which returns a sequence of length at most $b$ derived from $G$, as follows.

$$\text{SBFS}(G; b) = \begin{cases} \{g_i\}_{i=1}^n & \text{if } n \leq b \\ \{g_{f(k)}\}_{k=1}^\infty & \text{if } n > b \end{cases} \quad (1)$$

In Equation 1, $m(n, b)$ characterizes the number of buckets to be allocated to host video features, and is defined as $m(n, b) = \lfloor \frac{n}{\lceil n/b \rceil} \rfloor \leq b$, where $\lfloor \rfloor$, $\lceil \rceil$ are the floor and ceiling operators, respectively. The index $f(k)$ is sampled according to a uniform distribution over the indices of the features in the bucket, as Equation 2 shows, below.

$$f(k) \sim U_{\lfloor n/b \rfloor : \lceil n/b \rceil}^{\lfloor n/b \rfloor : \lceil n/b \rceil} \quad (2)$$

More intuitively, we create a fixed number of buckets and allocate features to each by equally distributing them into the buckets. During training, we randomly sample a single feature for each bucket, following a uniform distribution, effectively reducing the input sequence length to at most $b$, the number of buckets. When doing this, we also accordingly convert the original set of labels $\tau^s, \tau^e \in [1, \ldots, n]$ into $\bar{\tau}^s, \bar{\tau}^e \in [1, \ldots, b]$. For simplicity, without loss of generality, for the rest of the paper we will assume the sampling module always returns total of $b$ video features.

The nature of SBFS is that a single feature is sampled from each bucket with equal probability each time. If we assume features are i.i.d., this implies that the probability of getting a sampled video feature sequence is $P(G) = (b/n)^b$. As this is a very small probability, the number of potential distinct sampled video feature sets ($\bar{G}$) is exceptionally large. Fortunately, video features (frames) within a bucket are highly correlated as the original from neighboring video frames which are generally very similar, and one may make a weak assumption that bucket population in bucket $k$ may not contain sufficiently more information than any sampled feature $g_{f(k)}$ from the bucket population. In other words, if $g_{f(k)}$ is sufficient statistic of the bucket $k$, then any sampled video feature sequence $\bar{G}$ using SBFS contains sufficient statistics of $G$, and SBFS$(\bar{G})$ is the sufficient statistic of video feature population $G$. Therefore, we can make the following proposition.

**Proposition 1** Any sampled video feature sequence $\bar{G}$ from SBFS method is a sufficient statistic of video feature population $G$.

The above proposition is very important as it allows us to train any complex model, such as a Transformer, on very long videos using SBFS with adequate guarantees. Next, we also present an interesting insight on how to pool features within a bucket. To do this, let us denote the $j$-th dimension of the feature vector $g_i$ by $g^j_i$.

**Proposition 2** If the $j$-th dimension of vectors within the bucket $k$ has a uniform population for all $j$, i.e. $g^j_{f(k)}$ is uniformly distributed on $[1, \mu_j]$ where $\mu_j$ is unknown, by the Fisher–Neyman factorization theorem [14], the sufficient statistics of the population within the bucket $k$ is given by the max-pooling operator over the bucket features $^3$.

Although our SBFS procedure can also be applied during inference, founded by Proposition 2, it is better to decouple the model from this stochastic component and instead utilize max pooling operator over the features of the bucket at inference time. This gives models increased stability when predicting, without sacrificing performance, as we will show in §4.3.

### 3.3. Text encoding module

In the text encoding module, sentences are split using the BERT tokenizer, which also prepends the special CLS token, and adds the SEP marker at the end. Each token is mapped to learned embeddings of dimension $d_m$ and summed with learned positional encodings of the same size. These vectors are passed through $L$ encoder transformer blocks [44] with $M$ attention heads, to produce final text representations $[h_0, \ldots, h_m]$.

### 3.4. Localization module

As mentioned earlier, the localization module is a Transformer model that receives both textual and video features, previously obtained by the respective modules. For the former, we directly input $h_0, \ldots, h_m$, while for the latter we first project $\tilde{G} = [\tilde{g}_1, \ldots, \tilde{g}_b]$ into the hidden dimension using a trainable linear layer and further combine this with a set of learned positional encodings. These two encoded vector sequences are concatenated lengthwise and passed

---

Please check the supplementary material for details.
through $L$ encoder blocks [44] with $M$ attention heads, to produce $[h_0, \ldots, h_{m+6}]$.

From these vectors, we select $[h_{m+1}, \ldots, h_{m+k}]$ and utilize the same localization function proposed by [38] as the main training signal, namely, feature-level soft classification task on the time dimension. Concretely, two different MLP layers produce scores of each position being the start/end of the location, which are passed through a softmax activation to obtain $\hat{\tau}^s, \hat{\tau}^e \in \mathbb{R}^b$, which are compared to soft-labels using the Kullback-Leibler divergence ($L_{KL}$).

In order to guide the model to utilize the information in the relevant section of the video, we encourage the attention heads of this module to put more weight into the target video portions during training, adapt the approach proposed by [38] as shown below.

\[
L_{\text{att}} = -\sum_{l=1}^{L} \sum_{m=1}^{M} (1 - x \otimes x) \ast \log(1 - A^{l,m}) \quad (3)
\]

In Equation 3, $A^{(l,m)}$ is the the attention matrix of the $l$-th layer and $m$-th attention head of the localization module and $x \in \mathbb{R}^{n+k}$ is a vector that denotes which areas of the output sequence will be subject to our guiding signal, and is defined as $x = [1_m; \delta_{\tau^s \leq i \leq \tau^e}]$, where $\delta$ denotes concatenation, $\delta$ is the Kronecker delta returning 1 when $i$ is inside the range of $\tau$, and $1_k$ denotes a vector of ones of size $k$.

We also note that the localization loss proposed in [38] is not sensitive to the order of the predictions of the starting and ending locations, as there is no conditioning on the time in the model portions that generate them. To induce the model to respect this order, we take a probabilistic approach and push the expected of the start of the segment (S) to be before the expected value of the ending (E) location, which is equivalent to requiring $E(E) - E(S) > 0$. Replacing the values of the expectations, we obtain the following.

\[
E(E) - E(S) = \sum_{i=1}^{b} \hat{\tau}^s_i - \sum_{i=1}^{b} \hat{\tau}^e_i = \sum_{i=1}^{b} i(\hat{\tau}^e_i - \hat{\tau}^s_i) \quad (4)
\]

In Equation 4 above, $\hat{\tau}^s_i$ and $\hat{\tau}^e_i$ are integers that denote the predicted probability value of the starting and ending localizations at position $i$. Based on this derivation, we formally implement our loss by minimizing the negative difference of the expected values as shown in Equation 5, below.

\[
L_{\text{sc}} = \min(0, \sum_{i=1}^{b} i(\hat{\tau}^e_i - \hat{\tau}^s_i)) \quad (5)
\]

Finally, our model is trained with the direct summation of the three losses introduced earlier such that $\mathcal{L} = L_{KL} + L_{\text{att}} + L_{\text{sc}}$.

4. Experiments

4.1. Datasets

To evaluate our proposed approach, we work with three widely-utilized and challenging datasets. **Charades-STA:** Built upon the Charades dataset [41], which provides time-based annotations using a pre-defined set of activity classes, and general video descriptions. We use the predefined train and test sets, containing 12,408 and 3,720 moment-query pairs respectively. Videos are 31 seconds long on average, with 2.4 moments on average, each being 8.2 seconds long on average. **ActivityNet Captions:** Introduced by Krishna et al. [27], this dataset originally constructed for dense video captioning, consists of 20k YouTube videos with an average length of 120 seconds. The videos contain 3.65 temporally localized time intervals and sentence descriptions on average, where the average length of the descriptions is 13.48 words. Following the previous methods, we report the performance on the combined validation sets. **YouCookII:** Consists of 2,000 long untrimmed videos from 89 cooking recipes obtained from YouTube by Zhou et al. [62]. Each step for cooking these dishes was annotated with temporal boundaries and aligned with the corresponding section of the recipe. The average video length is 5.26 minutes. In terms of relevant moment segments, each video has 7.73 moments on average, with each segment being 19.63 seconds long on average.

4.2. Implementation Details

For our experiments, we consider an off-line video encoding function $F_V(V)$, following previous work [18, 37, 38, 45, 51, 52, 56]. Concretely, we first pre-process the videos by extracting features of size 1024 using I3D with average pooling, taking as input the raw frames of dimension $256 \times 256$, at 25fps. We use the pre-trained model trained on Kinetics for ActivityNet and YouCookII released by [7]. For Charades-STA, we use the pre-trained model trained on Charades. For the natural language input, we use the BERT-base-uncased tokenizer and keep the parameters of the Text Encoder fixed. Our experiments are performed on two GPUs, a 16-GB NVIDIA V100 and a 48-GB Quadro RTX 8000. Models are trained in an end-to-end fashion using ADAM [24].

Evaluation is based on two widely used metrics proposed by [15], namely the Recall at various thresholds of the temporal Intersection over Union (tIoU or $R^{\alpha \alpha}$) measuring the percentage of predictions that have tIoU with ground truth larger than certain $\alpha$, and the mean averaged tIoU (mIoU). We use three $\alpha$ threshold values 0.3, 0.5 and 0.7.

4.3. Ablation Studies

We begin by performing an extensive empirical study of our proposed stochastic sampling technique, comparing it to
several alternatives. We specifically consider the following sampling approaches.

**Random:** As a naive baseline, we randomly sample features from the video, maintaining the order.

**Fixed-rate video down-sampling (FRVS):** We experiment with I3D features extracted at a lower frame-rate of 5fps, a technique that has been utilized by previous work such as [18], which can be regarded as a form of low-level down-sampling.

**Fixed-rate feature down-sampling (FRFS):** We experiment with two fixed-rate down-sampling techniques at the feature level, bucket-level mean-pooling and max-pooling.

**Dynamic Time Warping (DTW):** We perform dynamic time warping between the non-structured video features and the fixed size temporal sequence created using our stochastic sampling technique and max-pooling applied inside each bucket. In this way, we assign features to each bucket that will later be randomly sampled.

**Dynamic-rate feature down-sampling (DRFS):** We utilize the similarity across features to dynamically create each bucket. While many variations are possible here, we decided to utilize a cosine distance-based heuristic to create the buckets. Please check the supplementary material for details.

**SBFS Variations:** Taking our proposed technique as a base, we experiment with different alternatives for inference. Concretely, we always apply our stochastic sampling during training, and either use it for inference as well (SBFS-all), or replace it with bucket-wise mean pooling (SBFS-mean) or max pooling (SBFS).

For the experiments, we combine each of these sampling approaches with the rest of the LOCFORMER architecture, and always use a bucket size of 200. Regarding the data, we use the YouCookII datasets, as contains videos that can be as long as 18 minutes, and contains queries that use rich language, which should help illustrate the importance of the sampling more clearly.

As the results in Table 1 show, the effectiveness of our sampling technique is clear, specially when compared with more naive alternatives like random sampling, or simple mean pooling. We see that low-level down-sampling techniques that extract fewer frames from the original video, are not effective either. In contrast, the naive version of the max-pooling-based sampling stands out, performing similarly but still below SBFS. These results helps illustrate the importance of the stochastic approach we have taken, which enables us to limit the input to the model while still exposing it to all of the training data in the long run, significantly improving its generalization capabilities. Finally, we also note that all the tested sampling alternatives except DTW and DRFS do not utilize information about the features when generating the buckets. It is interesting to see that many of these arguably simpler sampling techniques, including SBFS, outperform data-informed approaches.

Next, we study the impact of SBFS at different bucket sizes. For these experiments we use the YouCookII dataset.
which contains the longest videos on average, and test bucket sizes ranging from 100 to 500. As we can see on Table 2, variations on parameter $b$ have an impact consistent with its expected behavior, with diminishing results as $b$ increases, and a clear performance sweet-spot at $b = 200$ which we adopt for the rest of the experiments in this paper.

Finally, we ablate LoCFORMER component-by-component, comparing it with two highly-competitive Transformer-based model variations: (1) Transformer-base a randomly-initialized multi-modal Transformer-base, into which we directly feed the text input and the sampled video features, previously embedding them using a learned embedding matrix and a linear projection layer, respectively. Each encoder uses a separate set of positional embeddings, and we also add a type embedding to indicate the model the nature of each vector. After this, the embedded sequences are concatenated lengthwise and passed through the transformer blocks; (2) BERT-base, where we initialize our Transformer-base variation with the weights of BERT. In this case, the projection linear layer of the video features and the respective positional encodings are randomly initialized.

Both model variations apply our attention guiding loss $L_{att}$ to all the attention heads in all the layers. This effectively means that there is no functionality separation inside these models. We note that these baselines are comparable to existing multi-modal transformer models such as ViLBERT [33] and UNITER [11]. Experiments are again performed in YouCookII, which contains the longest videos.

As Table 3 shows, we see that LoCFORMER is able to consistently outperform our Transformer-based variations, with each ablated component clearly contributing to increased performance. The results also reflect the importance of SBFS, enabling all kinds of Transformer-based models we tested to process long untrimmed videos, which would otherwise lead to out-of-memory errors.

Regarding the interaction of the attention loss with dif-

| Method   | Charades-STA | ActivityNet | YouCookII |
|----------|--------------|-------------|-----------|
|          | R@0.3 | R@0.5 | R@0.7 | mIoU | R@0.3 | R@0.5 | R@0.7 | mIoU | R@0.3 | R@0.5 | R@0.7 | mIoU |
| Random   | -     | 8.51  | 3.03  | -    | 5.60  | 2.50  | 0.80  | -    | 4.84  | 1.72  | 0.60  | -    |
| CTRL     | -     | 21.42 | 7.15  | -    | 28.70 | 14.00 | -    | 20.54 | -    | -    | -    | -    |
| ABLR †   | -     | 24.36 | 9.00  | -    | 55.67 | 36.79 | -    | 36.99 | -    | -    | -    | -    |
| TriNet   | 51.33 | 36.61 | 14.50 | -    | 48.42 | 32.19 | 13.93 | -    | -    | -    | -    | -    |
| CBP      | 50.19 | 36.80 | 18.87 | 35.74 | 54.30 | 35.76 | 17.80 | 36.85 | -    | -    | -    | -    |
| MAN      | -     | 46.53 | 22.72 | -    | -    | -    | -    | -    | -    | -    | -    | -    |
| ExCL ‡   | 65.10 | 44.10 | 22.60 | -    | 62.10 | 41.60 | 23.90 | -    | 26.58 | 15.72 | 8.19  | -    |
| TMLGA    | 67.53 | 52.02 | 33.74 | 48.22 | 51.28 | 33.04 | 19.26 | 37.78 | 33.48 | 20.65 | 10.94 | 23.07 |
| LGVTI    | 72.96 | 59.46 | 35.48 | 51.38 | 58.52 | 41.51 | 23.07 | 41.13 | -    | -    | -    | -    |
| DORi     | 72.72 | 59.65 | 40.56 | 53.28 | 57.89 | 41.49 | 26.41 | 42.78 | 43.36 | 30.47 | 18.24 | 30.46 |
| VSLNet   | 70.46 | 54.19 | 35.22 | 50.02 | 63.16 | 43.22 | 26.16 | 43.19 | -    | -    | -    | -    |
| CPNet    | -     | -    | -    | -    | -    | 48.02 | 31.78 | -    | -    | -    | -    | -    |
| CPN      | 75.53 | 59.77 | 36.67 | 53.14 | 62.81 | 45.10 | 28.10 | 45.70 | -    | -    | -    | -    |
| MSAT     | -     | -    | -    | -    | -    | -    | -    | -    | -    | -    | -    | -    |
| OCFORMER | 71.88 | 58.52 | 38.51 | 51.76 | 60.61 | 43.74 | 27.04 | 44.05 | 46.76 | 31.33 | 15.81 | 30.92 |

Table 4. Performance comparison of our approach with existing methods for different tIoU α levels. Values are reported on the validation split of Charades-STA and the ActivityNet Captions. † Results for ABLR are as reported by [10]. ‡ The results reported by ExCL for ActivityNet have 3,370 missing videos, and the results on YouCookII were obtained using our own implementation.

| Data     | Model | Memory | Performance |
|----------|-------|--------|-------------|
|          |       | GB     | R@0.3 R@0.5 R@0.7 mIoU |
| Charades-STA | ExCL  | 2.8    | 62.28 39.73 22.53 42.28 |
|           | + SBFS| 1.6    | 62.74 42.04 24.57 43.05 |
|           | TMLGA | 2.3    | 67.53 52.02 53.48 42.26 48.22 |
|           | + SBFS| 1.5    | 70.67 52.20 33.90 49.18 |
|           | DORi  | 32.8   | 72.72 59.65 40.56 53.28 |
|           | + SBFS| 23.1   | 72.90 59.67 40.94 53.44 |
| ActivityNet | ExCL  | 6.4    | 55.49 39.33 24.04 40.32 |
|           | + SBFS| 1.8    | 56.42 40.37 24.70 41.13 |
|           | TMLGA | 7.3    | 51.28 33.04 19.56 37.78 |
|           | + SBFS| 1.7    | 53.00 35.10 19.83 37.85 |
|           | DORi  | 34.7   | 57.89 41.35 26.41 42.79 |
|           | + SBFS| 24.0   | 58.89 42.21 26.36 43.02 |
| YouCookII | ExCL  | 6.9    | 26.58 15.72 8.19 18.99 |
|           | + SBFS| 1.8    | 30.96 18.64 10.05 21.76 |
|           | TMLGA | 9.5    | 33.48 20.65 10.94 23.07 |
|           | + SBFS| 1.8    | 39.29 25.40 12.80 26.20 |
|           | DORi  | 46.4   | 43.36 30.47 18.24 30.46 |
|           | + SBFS| 24.2   | 46.74 32.19 18.33 31.69 |

Table 5. Results of our experiments combining SBFS with existing work. Except where indicated, experiments were performed using a batch size 32. † indicates experiments performed using a batch size of 4 due to memory constraints.
ifferent model variations, we see that this additional training signal leads to consistent gains for all Transformer-based variations, but that these are larger in the case of LOCFORMER. We surmise this is due to the attention loss potentially interfering with the inductive bias that the baselines require to process the multi-modal inputs, as well as with the already acquired bias in the case of BERT, reflected in certain attention patterns for each head which have been studied and documented by Rogers et al. [39] among others. This ultimately highlights the importance of separating functionality inside Transformer models for our task, which allows our model to perform better overall.

4.4. Comparison to state-of-the-art models

We compare the performance of LOCFORMER on the datasets considered against several prior work, as well as to a random baseline that simply selects an arbitrary video segment as the moment for each example. We consider a broad selection of models based on different approaches, specifically proposal-based techniques including CTRL [15], MAN [56], CBP [46] and the more recent multi-stage Transformer approach (MSAT) by Zhang et al. [38], as well as TripNet [21], a method based on reinforcement learning. In addition to that, we also compare our approach to more recent methods that do not rely on proposals, including ABLR [53], ExCL [18], TMLGA [38] and LGVTI [34], as well as more recent approaches including CPNet [29], VSLNet [57], CPN [59] and DORi [37]. These two last models contain specifically-crafted graph-based approaches for the task, with DORi also incorporating spatio-temporal features.

Table 4 summarizes our best results on Charades-STA, ActivityNet Captions and YouCookII datasets, while also comparing the obtained performance to relevant prior work. We can see that overall LOCFORMER is able to offer excellent performance, closing the gap with sophisticated graph-based models like CPN and DORi, and obtaining a new state-of-the-art in YouCookII, showing the effectiveness of our approach when dealing with long untrimmed videos.

4.5. Combining SBFS with previous work

We finally focus on studying the ability of our sampling technique to be combined with different models. We do this by incorporating SBFS into three proposal-free models selected from the literature, and testing them on our datasets. We consider ExCL [18] and TMLGA [38], which have been extensively studied in the past years, as well as DORi. We utilized our own implementation of ExCL with our I3D features extracted at 25 fps, and directly integrated the original implementations of the latter into our code.

As Table 5 shows, SBFS is able to consistently provide performance improvements in all cases, with gains of up to 3.13% in terms of the mean temporal IoU. These improvements lead to new state-of-the-art results on both the Charades-STA and YouCookII datasets. We note that despite not having access to the spatial information that DORi incorporates, the performance of LOCFORMER is very competitive to that of DORi+SBFS in YouCookII, which contains the longest videos. This again illustrates the effectiveness of our approach in this scenario.

4.6. Limitations and Societal Impact

Although our sampling technique has shown to be very efficient and effective in different datasets, there is a specific scenario where it could degrade the performance of a given model. This scenario occurs when the span of the query, a.k.a. moment, is located completely inside a given bucket, with many additional frames/features in the same bucket. In this case, the best that a model can do is that predict the moment happens inside of that bucket, losing finer granularity. In practice, this occurs when the ratio between the duration of a given moment and the duration of the video is vanishingly small. In terms of societal impact, models that excel at temporal moment localization could be used to break private information and manipulate people’s behavior. On the other side, the benefit of less memory usage reduces GPU power consumption and therefore could facilitate access to tasks related to videos for researchers with fewer resources.

5. Conclusion

In this paper we have presented LOCFORMER, a Transformer-based model for the task of temporal moment localization which operates at a constant maximum memory footprint regardless of the input length. The success of our model fundamentally relies on our modular design, which allows us to separate functionality, and SBFS, where we split the sequence of input video features into a fixed number of buckets and select a single feature per bucket using a stochastic approach. Experiments conducted on three challenging datasets show that LOCFORMER obtains excellent results, being able to obtain state-of-the-art performance on YouCookII. We also show that our sampling technique can improve the performance of prior work on all considered datasets, leading to a new state-of-the-art on Charades-STA. We think these results highlight the importance of sampling techniques as a valid mechanism to obtain better coverage of long input videos while keeping memory usage low.

For future work, we are interested in testing our sampling-based approach in other relevant tasks in the context of video-and-language, for example as video retrieval. We are also interested in extending our approach to address its limitations, for example, using adaptive or iterative sampling to treat different areas of the video with different granularity as required.
References

[1] Anurag Arnab, Mostafa Dehghani, Georg Heigold, Chen Sun, Mario Lučić, and Cordelia Schmid. ViViT: A Video Vision Transformer. arXiv:2103.15691 null, Mar. 2021.

[2] Iz Beltagy, Matthew E. Peters, and Arman Cohan. Longformer: The Long-Document Transformer. arXiv:2004.05150 [cs], Dec. 2020.

[3] Gedas Bertasius, Heng Wang, and Lorenzo Torresani. Is Space-Time Attention All You Need for Video Understanding? arXiv:2102.05905 [cs], Feb. 2021.

[4] Adrian Bulat, Juan-Manuel Perez-Rua, Swathikiran Sudhakaran, Brais Martinez, and Georgios Tzimiropoulos. Space-time Mixing Attention for Video Transformer. arXiv:2106.05968 [cs], June 2021.

[5] Fabian Caba Heilbron, Victor Escorcia, Bernard Ghanem, and Juan Carlos Niebles. Activitynet: A large-scale video benchmark for human activity understanding. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pages 961–970, 2015.

[6] Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In CVPR, 2017.

[7] Joao Carreira and Andrew Zisserman. Quo vadis, action recognition? a new model and the kinetics dataset. In CVPR, 2017.

[8] Yu-Wei Chao, Sudheendra Vijayanarasimhan, Bryan Seibold, David A. Ross, Jia Deng, and Rahul Sukthankar. Re-thinking the faster R-CNN architecture for temporal localisation. CVPR, 2018.

[9] Jingyuan Chen, Xinpeng Chen, Lin Ma, Zequn Jie, and Tat-Seng Chua. Temporally grounding natural sentence in video. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 162–171, Brussels, Belgium, 2018. Association for Computational Linguistics.

[10] Shaoxiang Chen and Yu-Gang Jiang. Semantic proposal for activity localization in videos via sentence query. AAAI, 2019.

[11] Yen-Chun Chen, Linjie Li, Licheng Yu, Ahmed El Kholy, Faisal Ahmed, Zhe Gan, Yu Cheng, and Jingjing Liu. UNITER: UNiversal Image-TEXT Representation Learning. In Andrea Vedaldi, Horst Bischof, Thomas Brox, and Jan-Michael Frahm, editors, Computer Vision – ECCV 2020, Lecture Notes in Computer Science, pages 104–120, Cham, 2020. Springer International Publishing.

[12] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. 2018.

[13] Victor Escorcia, Fabian Caba Heilbron, Juan Carlos Niebles, and Bernard Ghanem. DAPs: Deep Action Proposals for Action Understanding. In Bastian Leibe, Jiri Matas, Nicu Sebe, and Max Welling, editors, Computer Vision – ECCV 2016, Lecture Notes in Computer Science, pages 768–784. Springer International Publishing, 2016.

[14] Ronald A. Fisher. On the mathematical foundations of theoretical statistics. Philosophical Transactions of the Royal Soc-
[30] Tianwei Lin, Xu Zhao, and Zheng Shou. Single Shot Temporal Action Detection. In *Proceedings of the 25th ACM International Conference on Multimedia*, MM ’17, pages 988–996, New York, NY, USA, 2017. ACM. event-place: Mountain View, California, USA.

[31] Daizong Liu, Xiaoye Qu, Jianfeng Dong, and Pan Zhou. Adaptive Proposal Generation Network for Temporal Sentence Localization in Videos. *arXiv:2109.06398 [cs]*, Sept. 2021.

[32] Meng Liu, Xiang Wang, Liqiang Nie, Xiangnan He, Baoquan Chen, and Tat-Seng Chua. Attentive moment retrieval in videos. In *The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval*, pages 15–24. ACM, 2018.

[33] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alch´e-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 13–23. Curran Associates, Inc., 2019.

[34] Jonghwan Mun, Minsu Cho, and Bohyung Han. Local-Global Video-Text Interactions for Temporal Grounding. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 10807–10816, Seattle, WA, USA, June 2020. IEEE. 3, 8

[35] Seiichi Nakagawa and Hirobumi Nakanishi. Speaker-independent english consonant and japanese word recognition by a stochastic dynamic time warping method. *IETE Journal of Research*, 34(1):87–95, 1988.

[36] Alexander Richard, Hilde Kuehne, Ahsan Iqbal, and Juergen Gall. Neuralnetwork-viterbi: A framework for weakly supervised video learning. In *IEEE Conf. on Computer Vision and Pattern Recognition*, volume 2, 2018.

[37] Cristian Rodriguez-Opazo, Edison Marrese-Taylor, Basura Fernando, Hongdong Li, and Stephen Gould. DORI: Discovering Object Relationships for Moment Localization of a Natural Language Query in a Video. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 1079–1088, 2021.

[38] Cristian Rodriguez-Opazo, Edison Marrese-Taylor, Fatemeh Sadat Saleh, Hongdong Li, and Stephen Gould. Proposal-free temporal moment localization of a natural-language query in video using guided attention. *WACV*, 2020.

[39] Anna Rogers, Olga Kovaleva, and Anna Rumshisky. A primer in BERTology: What we know about how BERT works. *Transactions of the Association for Computational Linguistics*, 8:842–866, 2020.

[40] Zheng Shou, Dongang Wang, and Shih-Fu Chang. Temporal action localization in untrimmed videos via multi-stage cnns. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2016.

[41] Gunnar A. Sigurdsson, Gyl Varol, Xiaolong Wang, Ali Farhadi, Ivan Laptev, and Abhinav Gupta. Hollywood in homes: Crowdsourcing data collection for activity understanding. In *European Conference on Computer Vision*, 2016.

[42] Chendra Hadi Suryanto, Jing-Hao Xue, and Kazuhiro Fukui. Randomized time warping for motion recognition. *Image and Vision Computing*, 54:1–11, 2016.

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

[44] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in neural information processing systems*, pages 5998–6008, 2017.

[45] Jingwen Wang, Lin Ma, and Wenhao Jiang. Temporally Grounding Language Queries in Videos by Contextual Boundary-aware Prediction. *arXiv:1909.05010 [cs]*, Dec. 2019.

[46] Jingwen Wang, Lin Ma, and Wenhao Jiang. Temporally grounding language queries in videos by contextual boundary-aware prediction. *AAAI*, 2020.

[47] Sinong Wang, Belinda Z Li, Madian Khabsa, Han Fang, and Hao Ma. Linformer: Self-attention with linear complexity. *arXiv preprint arXiv:2006.04768*, 2020.

[48] Wenhao Wu, Dongliang He, Tianwei Lin, Fu Li, Chuang Gan, and Errui Ding. MvFnet: Multi-view fusion network for efficient video recognition. In *AAAI*, 2021.

[49] Zuxuan Wu, Caiming Xiong, Chih-Yao Ma, Richard Socher, and Larry S. Davis. Adaframe: Adaptive frame selection for fast video recognition. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.

[50] Huijuan Xu, Kun He, L. Sigal, S Sclaroff, and K Saenko. Multilevel language and vision integration for text-to-clip retrieval. In *AAAI*, 2019.

[51] Yitian Yuan, Lin Ma, Jingwen Wang, Wei Liu, and Wenwu Zhu. Semantic Conditioned Dynamic Modulation for Temporal Sentence Grounding in Videos. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alch´e-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems 32*, pages 536–546. Curran Associates, Inc., 2019.

[52] Yitian Yuan, Lin Ma, Jingwen Wang, Wei Liu, and Wenwu Zhu. Semantic conditioned dynamic modulation for temporal sentence grounding in videos. In *Advances in Neural Information Processing Systems*, pages 534–544, 2019.

[53] Yitian Yuan, Tao Mei, and Wenwu Zhu. To find where you talk: Temporal sentence localization in video with attention based location regression. *AAAI*, 2019.

[54] Rowan Zellers, Ximing Lu, Jack Hessel, Youngjae Yu, Jae Sung Park, Jize Cao, Ali Farhadi, and Yejin Choi. MERLOT: Multimodal Neural Script Knowledge Models. *arXiv:2106.02636 [cs]*, June 2021.

[55] Runhao Zeng, Haoming Xu, Wenbing Huang, Peihao Chen, Mingkui Tan, and Chuang Gan. Dense Regression Network for Video Grounding. *arXiv:2004.03545 [cs]*, Apr. 2020.

[56] Da Zhang, Xiyang Dai, Xin Wang, Yuan-Fang Wang, and Larry S Davis. Man: Moment alignment network for natural language moment retrieval via iterative graph adjustment. *CVPR*, 2019.
[57] Hao Zhang, Aixin Sun, Wei Jing, and Joey Tianyi Zhou. Span-based Localizing Network for Natural Language Video Localization. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 6543–6554, Online, July 2020. Association for Computational Linguistics. 3, 8

[58] Mingxing Zhang, Yang Yang, Xinghan Chen, Yanli Ji, Xing Xu, Jingjing Li, and Heng Tao Shen. Multi-Stage Aggregated Transformer Network for Temporal Language Localization in Videos. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 12669–12678, 2021. 2, 8

[59] Yang Zhao, Zhou Zhao, Zhu Zhang, and Zhijie Lin. Casco: A cascaded prediction network via segment tree for temporal language localization. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 6543–6554, Online, July 2020. Association for Computational Linguistics. 3, 8

[60] Yuan Zhi, Zhan Tong, Limin Wang, and Gangshan Wu. Mgsampler: An explainable sampling strategy for video action recognition. CoRR, abs/2104.09952, 2021. 3

[61] Luowei 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

[62] Luowei Zhou, Chenliang Xu, and Jason J Corso. Towards automatic learning of procedures from web instructional videos. In AAAI Conference on Artificial Intelligence, pages 7590–7598, 2018. 2, 5

A. Sufficient Statistic

A statistic is a function $T = r(X_1, \ldots, X_n)$ of the random sample $X_1, \ldots, X_n$, which carries information of the sampled data, such as the sample mean and sample variance. We say that a statistic satisfies the criterion of sufficiency when no other statistic which can be calculated from the same sample provides any additional information as to the value, of the parameter to be estimated. We can easily find a sufficient statistics by using the Fisher–Neyman Factorization Theorem.

Factorization theorem: given a random sample $X_1, \ldots, X_n$ with joint density $f(x_1, \ldots, x_n|\theta)$ a statistic $T = r(X_1, \ldots, X_n)$ is sufficient if and only if the joint density can be factored as follows:

$$f(x_1, \ldots, x_n|\theta) = u(x_1, \ldots, x_n)v(r(x_1, \ldots, x_n), \theta)$$

where $u$ and $v$ are non-negative functions. The function $u$ can depend on the full random sample $x_1, \ldots, x_n$ but not on the unknown parameter $\theta$. The function $v$ can depend on $\theta$, but can depend on the random sample only through the value of $r(x_1, \ldots, x_n)$.

In our case, let us assume that our bucket contains features $X_i$ that are independent and uniformly distributed on $[0, \theta]$ where $\theta$ is unknown. Then, the probability density function can be written as a product of individual densities since the observations are independent,

$$f(x_1, \ldots, x_n|\theta) = \frac{1}{\theta} 1_{\{0 \leq x_1 \leq \theta\}} \cdots \frac{1}{\theta} 1_{\{0 \leq x_n \leq \theta\}}$$

Here $1(E)$ is an indicator function. It is 1 if the event $E$ holds, and 0 if it does not. Now $x_i \leq \theta$ for $i = 1, \ldots, n$ if and only if $\max\{x_1, \ldots, x_n\} \leq \theta$. Therefore,

$$f(x_1, \ldots, x_n|\theta) = \frac{1}{\theta^n} 1_{\{0 \leq \min\{x_i\}\}} 1_{\{\max\{x_i\} \leq \theta\}}$$

Thus, the factorization theorem shows that $T = \max\{X_1, \ldots, X_n\}$ is a sufficient statistic since the density function takes the required form, where $u = 1_{\{0 \leq \min(x_i)\}}$ and $v = \frac{1}{\theta^n} 1_{\{\max\{x_i\} \leq \theta\}}$, which is a function that only depends on $\theta$ and $T = \max\{x_i\}$.

B. Dynamic-Rate Feature Down-Sampling

In this section, we present details of our Dynamic-Rate Feature Down-Sampling ablation experiments. With this sampling heuristic, our intention was to create buckets that satisfy the two following conditions. First, we would like each bucket to hold semantically similar features, using similarity on the embedding space as a proxy. Second, we aim to group features in a way such that the number of buckets $l$ that hold the totality of the features in the video is smaller than the desired number of buckets $b$. 

The bucket construction procedure works as follows. For an input feature sequence of length $n$, we use the cosine distance to compute the semantic similarity between each of the features in the video, and construct the pairwise distance matrix $D \in \mathbb{R}^{n \times n}$. We then start the process with a single bucket that contains only the first feature $x_1$, and add features to this bucket starting from $x_2$. Feature $x_2$ will be added to the bucket if and only if the cosine-distance $D_{1,2} < th$, where $th$ is a threshold parameter, and otherwise a new bucket is started and the process is repeated until all the features have been processed. Once this is done, we evaluate the number of buckets $l$ that were created, and if $l > b$, then we reduce the threshold $th$ by a small margin (0.01) and generate all the buckets again. This process is repeated until the $l \leq b$ condition is satisfied. Please see Algorithm 1 below, for additional details.

**C. Qualitative Results**

In this section, we present qualitative results of our method for each one of datasets we use for evaluation. Ground truth (GT) and predictions in Figures 3, 4 and 5 are in seconds.

**Algorithm 1** Dynamic-rate Feature down-sampling using cosine similarity Algorithm

- $D = 1 - \text{pairwise\_distances}(V)$
- $th = 1.0$
- $flag = True$
- index\_sample = {}$

```plaintext
while flag do
    indx = 0
    st = 0
    ed = 1
    for ed ← st to len(V) do
        s = $D_{st,ed}$
        if $s < th$ then
            samples\_in\_bucket = []
            for i ← st to ed do
                samples\_in\_bucket.append(i)
            end for
            index\_sample[indx] = samples\_in\_bucket
            st = ed
            indx = indx + 1
        end if
        if indx <= bucket\_size then:
            flag = False
        else
            th = th - 0.01
            index\_sample = {}
        end if
    end for
end while
```

As seen on Figure 3, in the case of ActivityNet Caption, our method is able to localize the query *The man continue to rub the board using his polishing tools* with a high temporal intersection over union (IoU) of 80.41%. Though not visible in the figure, we also note that the end of this video is full of black frames and information about the creator, e.g., webpage and logos. This exemplifies how ground truth annotations can be inaccurate, and how our model can adequately deal with these issues.

Figure 4 presents qualitative results for YookCookII dataset. In this case, we specifically present our predictions on one of the longest videos in the dataset, with a duration of 11 minutes and 46 seconds, and where the natural language query is *slice up the ginger finely*. As seen, our method obtains an impressive performance considering that the moment of interest lasts only 20 seconds. This figure also serves to exemplify one of the limitations of the bucketing approach we take. It is possible to see that the predictions of our model, though precise overall, add 0.96 seconds to both the start and end locations. This is a result of the maximum granularity given by the buckets and features in our system.

Finally, Figure 5 shows an example of the predictions of our model on the Charades-STA dataset. In this case, we also choose one of the longest videos in the data, with a duration of approximately 1 minute. For the query *person walks into room holding a bag*, our method obtains a good performance of 95.70% of temporal IoU.
Query: The man continue to rub the board using his polishing tools.

Figure 3. Results of our method on the ActivityNet dataset in a very long video of 12 minutes and 25 seconds (745.5 seconds). Our method can localize the query *The man continue to rub the board using his polishing tools* with a temporal IoU of 80.41%.

Query: slice up the ginger finely

Figure 4. Qualitative result of our method on the YouCookII dataset in one of the longest videos in the dataset (11 minutes and 46 seconds.) Our method obtains a temporal IoU of 90.83% for the query *slice up the ginger finely*.

Query: person walks into room holding a bag

Figure 5. Charades-STA qualitative results on one of the longest videos in the dataset. For the query *person walks into room holding a bag*, our method obtains 95.70% IoU with respect to the ground truth annotations.