Explore and Match: End-to-End Video Grounding with Transformer

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Abstract

We present a new paradigm named explore-and-match for video grounding, which aims to seamlessly unify two streams of video grounding methods: proposal-based and proposal-free. To achieve this goal, we formulate video grounding as a set prediction problem and design an end-to-end trainable Video Grounding Transformer (VIDGTR) that can utilize the architectural strengths of rich contextualization and parallel decoding for set prediction. The overall training is balanced by two key losses that play different roles, namely span localization loss and set guidance loss. These two losses force each proposal to regress the target timespan and identify the target query. Throughout the training, VIDGTR first explores the search space to diversify the initial proposals, and then matches the proposals to the corresponding targets to fit them in a fine-grained manner. The explore-and-match scheme successfully combines the strengths of two complementary methods, without encoding prior knowledge into the pipeline. As a result, VIDGTR sets new state-of-the-art results on two video grounding benchmarks with double the inference speed.

1. Introduction

The explosion of video data brought on by the growth of the internet poses challenges to effective video search. In order to accomplish successful video search, much effort has been put into language query-based video retrieval [9, 12, 30, 48, 49]. While text-video retrieval aims to match a trimmed video clip to the language query, video grounding aims to find accurate timespans relevant to the language queries in an untrimmed video. It can be helpful especially when one wants to find a specific scene in a long video, such as a movie. The majority of existing methods for video grounding can be categorized into two families: 1) proposal-based methods [2, 5, 13, 14, 17, 25, 26, 33, 43, 45, 48, 50, 54, 56, 57, 58], which generate a bunch of proposals in advance and select the best match with target spans, and 2) proposal-free methods [6, 7, 8, 15, 29, 31, 36, 42, 45, 52, 53, 55], which estimate start and end timestamps aligned to the given description directly. The proposal-based approaches generally show strong performance at the expense of prohibitive cost of proposal generation. They contradict the end-to-end philosophy, and their performances are significantly influenced by hand-designed pre- or post-processing steps such as dense proposal generation [10, 47] or non-maximum suppression [39, 45, 51] to abandon near-duplicate predictions. On the other hand, the proposal-free approaches are much more efficient, but involve difficulties in optimization since the search space for final timespan prediction is too large.

In this work, we present a new video grounding paradigm named explore-and-match, which integrates the strengths of the two aforementioned approaches by formulating video grounding as a direct set prediction problem.

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All codes and models will be made available shortly.

Figure 1. (a) Proposal-free methods directly regress start and end timestamps. (b) Proposal-based methods exhaustively match all predefined fixed-size proposals with ground truths. (c) Our explore-and-match paradigm unifies two methods, eliminating the hand-crafted proposals, and instead makes flexible timespan proposals. Unlike previous methods that predict one sentence in a single loop, our approach predicts multiple sentences at once.
Our method keeps the use of proposals while flexibly predicting timespans. Also, it eliminates time-consuming pre- and post-processing via a direct set prediction. A conceptual comparison of our approach with two approaches is shown in Fig. 1. To solve video grounding as a set prediction problem, we introduce an end-to-end trainable model called VidGTR based on the transformer encoder-decoder architecture [41]. The primary ingredients of VidGTR are bipartite set matching and parallel decoding with a small set of learnable proposals. We refer to trainable positional encodings as learnable proposals that are transformed in parallel into timespans by the transformer decoder. To train all learnable proposals in parallel, we adopt the Hungarian algorithm [21] to find the optimal bipartite matching (i.e., paired in a way that minimizes the matching cost) between ground truths and predictions. This guarantees that each target has a unique match during training. The self-attention mechanism of the transformer enables all elements in an input sequence to interact with one another, making transformer architecture particularly suitable for certain constraints of set prediction, such as suppressing duplicate predictions. By design, VidGTR allows us to forgo the use of manually-designed components (e.g., temporal anchors, windows) that encode prior knowledge into the video grounding pipelines. Furthermore, learnable proposals can interact with visual-linguistic representations as well as themselves to directly output the final timespan predictions in a single pass.

In our explore-and-match scheme, all learnable proposals diversify while exploring span space, and subsequently match their corresponding targets. However, the model becomes unable to associate each prediction with an individual target since the transformer architecture does not encode positional information of the input sequence (i.e., target-agnostic). The overall training is governed by bipartite set matching with span localization loss and set guidance loss. The span localization loss leads proposals to predict precise timespans. On the other hand, set guidance loss makes VidGTR generate the target-specific predictions. We generate subgroups by dividing the learnable proposals by the number of sentences. Then, our set guidance loss gradually force each subset of proposals to predict the input order of the corresponding language query. At the beginning of training, each ground truth is assigned with a random proposal since set matching is largely driven by the span localization loss. Once the timespan proposals align with ground truths in a target-agnostic manner, the set guidance loss becomes dominant, and learnable proposals begin to predict the timespan of the designated target. Finally, the learnable proposals are fit to their respective target spans. The overall prediction-target matching is trained in a set-to-set manner. While the strategy conforms to the end-to-end basis, it spontaneously divides and conquers the entire process instead of optimizing all the objectives as a whole. Under the explore-and-match scheme, VidGTR starts by generating diverse initial timespan proposals that are target-agnostic, which are then regressed to match the specific target accurately. With set-to-set matching, the proposals in different subsets can peek at each other and cooperatively build an optimal set of timespans. We show the empirical evidence of the explore-and-match phenomenon and confirm that this simple strategy is remarkably effective.

We evaluate VidGTR trained under explore-and-match regime on two challenging video grounding benchmarks — ActivityCaptions [3, 20] and Chrades-STA [13] — against the recent works. Our VidGTR achieves new state-of-the-art results on two benchmarks, even without human priors such as knowledge of timespan distribution. In addition, we conduct extensive ablation studies and analyses on our method. To summarize, our contributions are three-fold:

- We introduce a new video grounding paradigm, “explore-and-match”, which unifies the strengths of proposal-based and proposal-free methods.
- We propose an end-to-end trainable model, VidGTR, which models the video grounding as a set prediction problem. This formulation streamlines the overall pipeline by removing the use of several heuristics.
- Comprehensive experiments and extensive ablation studies demonstrate the effectiveness of VidGTR. Moreover, VidGTR sets a new state-of-the-art on two video grounding benchmarks while being two times faster than previous methods.

2. Related Work

Video Grounding. The origin of video grounding traces back to the temporal activity localization [37], which attempts to locate the start and end timestamps of actions and identify its labels in an untrimmed video. Likewise, video grounding aims to retrieve the corresponding timespans, but it is grounded on language queries rather than a fixed set of action labels. Pioneering video grounding works [2, 13] define the task and provide benchmark datasets. Since then, numerous efforts have been made to push the boundaries of video grounding. Early works follow the proposal-based pipeline [2, 5, 13, 14, 17, 25, 26, 33, 43, 45, 48, 50, 54, 56, 57, 58], which segments a huge number of candidate timespans at regular intervals on different scales, and then ranks them using an evaluation network. While proposal-based approaches show reliable results, they are sensitive to proposal quality and suffer from the prohibitive cost of creating proposals, as well as the computationally inefficient comparison of all proposal-target pairings. Another line of works are the proposal-free approaches [6, 7, 8, 15, 29, 31, 36, 42, 45, 52, 53, 55], which tries to regress the timespans directly. They are more flexible than proposal-based approaches in terms of granularity.
However, its accuracy generally lags behind that of its counterpart. To summarize, the former try to match the predefined proposals with ground truth, while the latter explore the whole search space to find timespans directly.

In this work, we aim to integrate two streams of video grounding methods into a single paradigm named explore-and-match, by formulating video grounding as a direct set prediction problem. Our method can generate flexible timespans like proposal-free approaches while preserving the concept of proposal-based approaches that use positive and negative proposals at the same time.

Transformers. A transformer [41] is an universal sequence processor with an attention-based encoder-decoder architecture. The self-attention mechanism captures both long-range interactions in a single context, and the encoder-decoder attention takes into account of token correspondences across multi modalities. Due to the tremendous promise of the attention mechanism, transformers have recently demonstrated their potential in various computer vision tasks: object detection [4], video instance segmentation [46], panoptic segmentation [44], human pose and mesh reconstruction [23], lane shape prediction [27], and human object interaction [59].

Among these, it is worth noting that the Detection Transformer (DETR) [4], the first transformer-based end-to-end object detector, achieved very competitive performance despite its simple design. DETR successfully removes many hand-crafted components in the object detection pipeline by exploiting the powerful relation modeling capability of transformers. The principal loss of DETR is based on bipartite matching, notably the Hungarian algorithm [21], which generates a set of unique bounding boxes. This saves a lot of post-processing time by removing non-maximum suppression from the pipeline. Also, DETR infers a set of predictions in parallel with a single iteration through the decoder.

Inspired by the recent successes of transformers, we propose a novel video grounding model named VidGTR based on the transformer architecture. The attention mechanism of transformers allows every element of the input sequence to attend to each other while utilizing rich contextualization. This architectural strength makes transformer particularly suitable for our video grounding formulation, a direct set matching problem. We note that final timespan predictions are directly generated in an end-to-end manner.

3. Method

We first define the video grounding task, and propose our end-to-end trainable VidGTR. Next, we introduce our training losses and set matching scheme. Finally, we present explore-and-match, a new paradigm that unifies proposal-based and proposal-free methods.

3.1. Problem Formulation

Video grounding aims to localize a set of language-grounded timespans in an untrimmed video. Since video grounding does not have a fixed set of sentence classes, the conventional classification approach is not applicable (i.e., taxonomy-free). Therefore, the video grounding model should be able to infer the timespans while not being constrained by the predefined categories. Formally, given a video $V$ with a set of language queries $Q = \{ q_i \}_{i=1}^K$, we require a set of corresponding timespans:

$$\{ \hat{y}_i \}_{i=1}^K = \{ (t_i, \hat{q}_i) \}_{i=1}^K ,$$

where $t_i = (t_i^s, t_i^e) \in [0, 1]$ defines start and end timestamp normalized by the video length, and $K$ is the number of the queries. If $K = 1$, the model only expects a single sentence as an input query, which is a conventional single-query setting. In this setting, there is no need for prediction-query assignment since all the predictions of learnable proposals can be associated with only one target (i.e., $q_i$ can be omitted in (1)). However, this limits the abundant interactions of the transformer with parallel decoding. In order to account for beneficial semantic and temporal relationships between the timespans, we view video grounding as a direct set prediction problem. In a multi-query setting, the model needs to specify which predictions are paired with which queries. Therefore, the grounding model should assign correct queries to the estimated timespans:

$$\{ \hat{y}_i \}_{i=1}^N = \{ (\hat{t}_i, \hat{q}_i) \}_{i=1}^N ,$$

where $\hat{t}$ and $\hat{q}$ denote the predicted timespans and queries, respectively. The number of predictions $N$ is substantially larger than the actual number of queries $K$ in the video.

3.2. VidGTR Architecture

The overall pipeline of VidGTR is illustrated in Fig. 2. VidGTR contains three main components: 1) a feature extractor to obtain a compact video and text representations, 2) a transformer encoder-decoder for contextualization and parallel decoding, and 3) a feed-forward network (FFN) that makes the final span predictions.

**Feature Extractor.** An input video $V \in \mathbb{R}^{T_0 \times C_0 \times H_0 \times W_0}$ passes through the C3D [40] (typical values we use are $T_0 = 16, C_0 = 3$ and $H_0 = W_0 = 112$), and is transformed into a video feature $f_v \in \mathbb{R}^{T \times C \times H \times W}$ ($T = 1, C = 512$ and $H = W = 4$). Since the input to transformer encoder should be in the form of sequence, we collapse the channel and spatial dimensions into a single dimension ($T \times CHW$). Then, we feed the output into a linear layer, which yields $T \times D$ dimensions. On the other hand, input language queries $Q$ break down into a set of word sequences, and then are converted into GloVe [32] embeddings. A set of sentence representations $f_s \in \mathbb{R}^{K \times D}$ ($K \geq 1, D = 512$) is obtained via a 2-layer bi-LSTM [18], followed by a linear
layer. The input sentences are batch-processed by applying zero-padding to have the same dimension $K$ as the largest number of sentences within the batch. For a fair comparison, VIDGTR is equipped with a conventional 3D+LSTM backbone, but it can be trained on top of any modern backbone (e.g., CLIP \cite{radford2021learning}, ViT \cite{dosovitskiy2021an}).

**Video Grounding Transformer.** The video features and text features obtained from the feature extractor. We concatenate video-text features and pass into the transformer encoder. The transformer\(^1\) is unable to preserve the order of temporally arranged video features due to the permutation-invariant nature of the architecture. Therefore, we add fixed positional encodings to concatenated video-text features at every attention layer. Each encoder layer has two sub-layers: a multi-head self-attention layer and a feed-forward network. The key component of the encoder is self-attention, which relates different positions of a single sequence to compute an intra-representation of the sequence. The decoder structure adds encoder-decoder attention in addition to the two sub-layers in the encoder. The decoder takes a fixed-size set of $N$ inputs, which we refer to as learnable proposals, and decodes them into a set of $N$ output embeddings. All proposals collaboratively generate predictions in a set-wise manner with self-attention while being able to access the whole video-text context with encoder-decoder attention. The output embeddings from the decoder are fed into the prediction head, resulting in $N$ final timespan predictions. The prediction head is a 2-layer perceptron with a two-dimensional output, which is set to predict start and end timestamps. To match the proposals to corresponding sentences, we measure their correspondence with normalized similarity of the decoder output and textual output of the encoder. This is used to link each prediction to the query with the highest similarity.

\(^1\)The architectural details of the transformer are elaborated in the supplementary material.

\section{3.3. Explore and Match}

Considering that video includes multiple events over various time periods, we define video grounding as a set prediction problem. To solve a set prediction problem between predicted and ground truth spans, we adopt a Hungarian matching algorithm \cite{kuhn1955hungarian}. Based on the matching results, we define our final set prediction loss. Finally, we present a new training paradigm named explore-and-match. We then elaborate on how it can combine two streams of methods, proposal-based and proposal-free.

**Video grounding as a set prediction.** We search for one-to-one matching between the prediction set $\{\hat{y}_i\}^N_{i=1}$ and the ground truth set $\{y_i\}^K_{i=1}$ that optimally assigns predicted timespans to each ground truth. We assume that the number of predictions $N$ is sufficiently larger than the number of queries $K$ in the video. Therefore, we consider the ground truth set $y$ as a set of size $N'$ padded with $\emptyset$ (no matching) for one-to-one matching. We define a set of all permutations that consist of $N$ items as $\mathcal{S}_N$. Among the set of permutations $\mathcal{S}_N$, we seek an optimal permutation $\hat{\sigma} \in \mathcal{S}_N$ that best assigns the predictions at the lowest cost:

$$\hat{\sigma} = \arg\min_{\sigma \in \mathcal{S}_N} \sum_{i=1}^{N} c_{\text{match}}(y_i, \hat{y}_{\sigma(i)}) ,$$

where $c_{\text{match}}(y_i, \hat{y}_{\sigma(i)})$ is a pair-wise matching cost between ground truth $y_i$ and a prediction with index $\sigma(i)$. We detail the matching cost in (8).

**Set guidance loss.** By the permutation-invariant nature of the transformer, the prediction order cannot be determined. This raises a question: how can we match the predictions with corresponding queries? To answer the question, we introduce a set guidance loss that forces each prediction to associate with a specific sentence query. Given $K$ input queries, $N$ proposals are uniformly partitioned into $K$ subsets. The proposals within the $j$th subset are trained to
simply defined as a negative log-likelihood loss: for the prediction with index $\sigma_i$ match spans are in the process of aligning with the targets, but they are nor order is accurate. (b) During the search space exploration, the spans are in the process of aligning with the targets, but they are unordered. (c) After proposals match the corresponding targets, the predicted spans are accurately aligned with the paired targets.

Figure 3. Visualization of timespan predictions (left) and prediction-query correspondences (right) at three different points in the training curves (top): (a) At early training, neither spans nor order is accurate. (b) During the search space exploration, the spans are in the process of aligning with the targets, but they are unordered. (c) After proposals match the corresponding targets, the predicted spans are accurately aligned with the paired targets.

predict the $j$th query by set guidance loss. Formally, we denote the probability that the prediction corresponds to the target query $q_i$ (i.e., softmaxed correspondence) as $\hat{p}_\sigma(i) (q_i)$ for the prediction with index $\sigma(i)$. The set guidance loss is simply defined as a negative log-likelihood loss:

$$L_{sg}(q_i) = -\sum_i \log \hat{p}_\sigma(i) (q_i).$$

While all proposals collaboratively predict a set of timespans via parallel decoding, the set guidance loss leads proposals to predict target-specific timespans.

**Span localization loss.** Our span localization loss is a linear combination of the $\ell_1$ loss and the generalized IoU (gIoU) loss [35]:

$$L_{\text{span}}(t_i, \hat{t}_\sigma(i)) = \lambda_{L1} L_{L1}(t_i, \hat{t}_\sigma(i)) + \lambda_{iou} L_{iou}(t_i, \hat{t}_\sigma(i)),$$

where $\hat{t}_\sigma(i)$ is the predicted timespan for the prediction with index $\sigma(i)$, and $\lambda_{L1}, \lambda_{iou} \in \mathbb{R}$ are balancing hyperparameters. While two loss terms share the same objective, they have subtle differences. The $\ell_1$ loss will have different scales for short and long timespans, even if relative errors are similar, whereas gIoU loss is robust to varying scales.

$$L_{L1}(t_i, \hat{t}_\sigma(i)) = ||t_i - \hat{t}_\sigma(i)||_1 + ||\hat{t}_\sigma(i) - \hat{t}_\sigma(i)||_1,$$

$$L_{iou}(t_i, \hat{t}_\sigma(i)) = \frac{|T(t_i, \hat{t}_\sigma(i)) \cap t_i \cup \hat{t}_\sigma(i)|}{|T(t_i, \hat{t}_\sigma(i))|}.$$

|\,| means temporal area and \,\setminus means set subtraction. \,\cup and \,\cap are used for union and intersection of timespans. $T(t_i, \hat{t}_\sigma(i))$ is a tight bound of span containing $t_i$ and $\hat{t}_\sigma(i)$.

**Final set prediction loss.** Both the target query prediction and timespan prediction are factored into the matching cost. We define matching cost using these notations:

$$L_{\text{match}}(y_i, \hat{y}_{\sigma(i)}) = -\mathbb{I}_{(q_i \notin \emptyset)} \hat{p}_\sigma(i) \mathbb{I}_{q_i \neq \emptyset} L_{\text{span}}(t_i, \hat{t}_\sigma(i)),$$

where $\mathbb{I}$ indicates the indicator function. Here, we consider the $K$ matched predictions as positives (i.e., $q_i \neq \emptyset$), and the remaining ($N - K$) predictions as negatives (i.e., $q_i = \emptyset$). Contrary to the loss, we do not use the negative log likelihood for the set guidance loss, but rather approximate it to $1 - \hat{p}_\sigma(i) (q_i)$. We omit a constant 1 since it does not change the matching. Based on the matching results, our final set prediction loss is defined as:

$$L_{\text{set}}(y_i, \hat{y}) = \sum_{i=1}^{N} [\lambda_{sg} L_{sg}(q_i) + \mathbb{I}_{(q_i \neq \emptyset)} L_{\text{span}}(t_i, \hat{t}_\sigma(i))].$$

where $\lambda_{sg}$ is a loss coefficient. Only the positives are optimized to predict the corresponding ground truth timespans.

**Unifying two streams of methods.** Our approach inherits only the advantages from the proposal-based and the proposal-free methods. We use the proposals, the core concept of the proposal-based methods, to encourage positive proposals to have higher similarities and suppress the negative proposals to have lower similarities with ground truth. However, since proposal-based methods view video grounding as a classification problem, their performances are largely limited by hand-crafted components, such as predefined anchors and windows. Our approach differs from the proposal-based methods in that it incorporates the flexibility of proposal-free methods. We make every proposal learnable, allowing them to be fine-tuned within the
training pipeline and dynamically transformed into more reliable proposals without the need for heuristics.

In order to put two complementary properties into a single model, we employ two losses: set guidance loss and span localization loss. The combination of all training schemes condenses into a new video grounding paradigm named explore-and-match. As shown in Fig. 3, the set guidance loss and the span localization loss tend to show different patterns in training curves, where the former generates a cliff-like loss curve and the latter degrades smoothly. At the beginning of the training (Phase I: Fig. 3(a)), predicted timespans are almost a random initialization without order. Before the sharp drop of a set guidance loss (Phase II: Fig. 3(b)), a set of timespans aligns with a set of ground truths in a target-agnostic manner. Interestingly, as the set guidance loss decreases, the $\ell_1$ loss and $\text{IoU}$ loss rebound slightly to reorganize predictions to be target-specific. When all losses converge (Phase III: Fig. 3(c)), timespans become accurate to match the target query. We empirically found that our method leads proposals to explore the search space, and then try to accurately match the target. We note that the whole process is carried out in a systematic and holistic manner.

4. Experiments

We first describe our experimental settings. Next, we report our main results on two challenging benchmarks: ActivityCaptions and Charades-STA. Lastly, we provide detailed ablation studies on the model variants and losses, and analyze how VIdGTR works with visualizations. \(^2\)

4.1. Experimental Setup

Datasets. 1) ActivityCaptions [3, 20] contains about 20K untrimmed videos with language descriptions and temporal annotations, which was originally developed for the task of dense video captioning [20]. Following the convention, we use $val_1$ for validation and $val_2$ for testing since the test annotations are not publicly released. We also follow the standard split [52]. 2) Charades-STA [13] is built on Charades [38] and contains 6,672 videos of daily indoors activities. Each video is about 30 seconds long on average. We employ 12,408 video-sentence pairs for train and 3,720 pairs for test, as in previous studies.

Evaluation metrics. Following [29, 52], we adopt two standard evaluation metrics for video grounding: 1) “R1@$\mu$”, which denotes the percentage of test samples that have at least one correct result in top-$\alpha$ retrieved results, \textit{i.e.}, Recall. Here, the correct results indicate that IoU with ground truth is larger than threshold $\mu$. 2) “mIoU”, which averages the IoU between predictions and ground truths over all testing samples to compare the overall performance.

\(^2\)We provide additional experiments in the supplementary material.

![Figure 4](image-url) Figure 4. VIdGTR achieves 10% of performance gain for R1@0.5 metric while being 2× faster than previous baselines on ActivityCaptions dataset. The average inference speed is measured by the number of localized sentences per second.

Technical details. We train VIdGTR using AdamW [28] with an initial learning rate of 1e-4 and weight decay of 1e-4 for a batch size of 16. We use a linear learning rate decay by a factor of 10. We consider Xavier initialization [16] to set the initial values of all transformer weights. We use 64 frames that are uniformly sampled from video with four sentences as an input. We resize every frame to $112 \times 112$. The number of learnable proposals is proportionally set to 10 times the number of input queries. For a fair evaluation with baselines, we extract video representations with C3D [40] pretrained on Sports-1M [19], and for the language part, we initialize each word with GloVe embeddings [32] and obtain sentence representation via 2-layer bi-LSTM [18]. In training, we set our overall loss weight $\lambda_{\text{IoU}} : \lambda_{\text{sg}} : \lambda_{\text{gg}}$ to 1 : 3 : 2. We also use an auxiliary decoding loss [1] in decoder layers to speed up the convergence. The initial proposals are filled with learnable weights [4].

4.2. Main Results

Comparison with state-of-the-art approaches. We compare VIdGTR against recently proposed video grounding methods, which can be largely categorized into three groups: 1) \textit{proposal-based}: CTRL [13], TGN [5], 2DTAN [57], CSMGAN [25], MSA [56]. 2) \textit{proposal-free}: ABLR [52], DEBUG [29], DRN [53], VSLNET [55], CP-NET [22], and 3) \textit{etc.}: BPNet [47], CBLN [24]. VIdGTR with C3D backbone, named VIdGTR-C3D, sets new state-of-the-arts on two benchmarks (see Table 1): ActivityCaptions [3, 20] and Charades-STA [13]. Especially for R1@0.5 metric on ActivityCaptions dataset, VIdGTR-C3D achieved about 10% performance gain compared to CBLN [24]. We further improve the performance of VIdGTR by using CLIP [34] as a backbone, \textit{i.e.}, VIdGTR-CLIP, where a massive amount of image-text pairs are pretrained with contrastive learning. Even freezing the back-
Table 1. Comparison with the state-of-the-arts on two benchmark datasets: ActivityCaption and Charades-STA. PB and PF denote proposal-based and proposal-free approaches, respectively.

Table 2. Ablation results of the loss functions.

Table 3. Choices for pred-query correspondence measure.

most the same results. When either L1 or gIoU losses is disabled, performance suffers significantly, implying that they are both required for accurate timespan localization. As using all three losses yields the best result, we confirm that two sub losses of span localization loss (L1 and gIoU) operate complementarily with absolute or relative criteria for timespan prediction.

Correspondence measures. We compare the various measures to calculate the correspondence between prediction and query in Table 3, which is then used in set guidance loss. In practice, we consider proposal-target matching using decoder output and textual part of encoder output. The encoder-decoder attention weight (Att) is an intuitive way to determine which part of the encoder output each proposal corresponds to. Since it has direct access to the global context, it performs well especially for the R5 metric, but falls short for the rigorous R1 metric. We see that using cosine similarity (Cos) dramatically improves performance than directly applying dot product similarity (Sim), meaning that removing the size constraint eases optimization.

Model size. To examine the effect of model size, we vary the number of transformer encoder-decoder layers (see Table 4). We first compare the two asymmetric structures (#Enc-#Dec): 2-1 vs. 1-2. Compared to the former, the latter falls 2.18 points in R5@0.5 and 6.33 points in R5@0.7 metrics, showing that the contextualization in encoder is important in generating high-quality proposals. As the size of the transformer increases, the R1 metric gradually improves, while R5 does not change appreciably. This suggests that increasing the size of the transformer has the effect of focusing on selecting better prediction among the candidates. However, considering that the performance degrades in 6-6, stacking more encoder-decoders does not always guarantee higher performance. Among several variants, we found that 4-4 shows the optimal performance.

Number of learnable proposals. We search for the optimal number of proposals per language query in Table 5. A
small number of proposals limits sufficient interactions between positives and negatives, resulting in sub-optimal performance, whereas an excessive quantity of proposals reduces accuracy by generating too many negatives. There is a trade-off between R5 and mIoU metrics around the appropriate number of proposals. Between them, having 10 learnable proposals per query yielded the best results.

Qualitative examples. In Fig. 9, we show a sample video grounding result, where the bars lie along the time axis represent the timespans grounded on the query. The predictions (color bar) generated by VIdGTR align with the target timespans (empty bar). As seen in the proposal-video attention map, we observe that the areas that learnable proposals mostly attend to are roughly divided by the number of queries; for example, the third prediction focuses on the end of the video. This means that proposals within the same subset consider similar parts of the video contexts in order to predict the target query.\footnote{More qualitative results are presented in the supplementary material.}

Distribution of learnable proposals. We visualize the timespan predictions of learnable proposals in Fig. 6. We observe that 10 out of all learnable proposals in the VIdGTR decoder mostly showed different patterns, which implies that VIdGTR learns different specializations for each proposal. More specifically, each proposal has several operating modes attending to different time zones and durations. For example, the top third proposal learns about a long period of time at the beginning of the video. Overall, all proposals have a mode that predicts video-wide durations, which is colored in blue.

5. Conclusion

In this study, we introduced explore-and-match, a new video grounding paradigm that unifies proposal-based and proposal-free approaches; our approach inherits the former concept while proposals are flexible as in the latter. We view video grounding as a direct set prediction problem. An end-to-end trainable VIdGTR is designed to solve this problem on top of transformer encoder-decoder architecture. VIdGTR predicts timespans in parallel, which are grounded on abundant video-text contexts. We employ bipartite matching in tandem with two key losses: 1) set guidance loss, which forces to match the target, and 2) span localization loss, which regresses each proposal to fit the timespan. Our approach diversifies proposals in the explore step and matches each proposal to specific sentence in the match step. VIdGTR achieves new state-of-the-art results on two challenging benchmarks while doubling the inference speed. We hope our exploration and findings facilitate future research on video grounding.
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A. Appendix

A.1. Architectural Details

We detail the architecture of VIDGTR in Fig. 7. The overall design is similar to that of original transformer encoder-decoder. First, the transformer encoder processes video-text features, which are extracted from the backbone, added with temporal positional encoding at each multi-head self-attention layer. Next, the decoder receives learnable proposals and encoder memory and process them with multiple multi-head self-attention and encoder-decoder attention layers. Finally, the output of decoder is used to generate the final set of predicted timespans, and also used to measure the correspondence between proposals and text queries.

A.2. Additional Experiments

Loss hyperparameters. We search for optimal loss hyperparameters in Table 6. We begin by setting the loss coefficients to 1:1:1 by default. While set guidance loss ($\lambda_{sg}$) is essential for query identity matching, the span localization loss ($\lambda_{L1}$ and $\lambda_{iou}$) directly affects the accurate video grounding. This can be confirmed by varying the coefficient for each term to 2 one-by-one. Among the three variations, we found that gIoU loss ($\lambda_{iou}$) is the most important term in the loss function. This is because the relative measure is more robust to varying spans shifted over various time distributions. While maintaining the gIoU loss to hold the major term, 1:3:2 yields the best results in our setting.

Input analysis. In order to examine the effect according to the number of input video frames and the number of input sentences, we varied the numbers in Table 7 and Table 8, respectively. As we expect more frames to bring more temporal knowledge, too few frames miss the exact moment when the event occurs, leading to decrease in performance. However, the results reveal that a large number of frames does not always guarantees better results. This implies that adding more frames cause a trade-off in the optimization while increasing the sequence length. We found that 64 produces the best results. Using multiple sentences as input queries allows us to take advantage of the temporal contexts between language queries. In the R1 metric, using 4 sentences as an input outperforms using 3 sentences, while using 3 sentences as an input shows better results in the R5 metric. This is due to the fact that the average number of existing sentences in training split of ActivityCaptions is 3.739. We adopt 4 sentences as an input since we require a more accurate model on a stricter metric.

Positional encodings. In Table 9, we ablate the positional encodings used by VIDGTR. First, we disable positional encoding for both video and text input. As expected, temporally unorganized input severely degrades performance. The positional encoding of each modality input is then removed in turn. When the video positional encodings are disabled, the model is no longer able to utilize temporally coordinated video contexts. In addition, the temporal clue provided by textual positional encoding is significant in textual input since it aids in organizing the order of events. We use both positional encodings since both positional encoding largely contributes to the performance. In order to align the video and text in a different time axis, we employ two separate positional encodings for each modality input.

Training with explore-and-match scheme. In Fig. 8, we investigate the behavior of VIDGTR during training under the explore-and-match scheme. Starting from random initialization, the predictions starts to create some variations. Since then, they have become a state that can be adapted to any timespan by slightly overlapping the boundaries of several ground truths, and then attempt to match only the span to some extent regardless of its identity. After matching the identity, we observe that the predictions try to accurately fit the corresponding span in a fine-grained manner. We argue that this systematic behavior is carried out by a carefully designed training regime.

4We use a fixed absolute encoding to represent the temporal positions.
Input Video

Input Queries

Query1: Three scuba divers are … camera panning all around the ocean.
Query2: Several shots … taking off their mask and waving to the camera.
Query3: In the end the divers come to the surface.

GT

Predictions

Figure 8. Visualization of predictions throughout training under explore-and-match scheme. Here, each row in predictions is represented in color — the brighter the color, the higher the probability of predictions — by overlapping the proposals that predict the corresponding query. The more overlapping the timespans predicted by the proposals, the brighter they become.

| #Frames | R1@0.5 | R1@0.7 | R5@0.5 | R5@0.7 | mIoU |
|---------|--------|--------|--------|--------|------|
| 16      | 47.93  | 23.34  | 72.30  | 51.31  | 42.53|
| 32      | 52.15  | 28.77  | 74.01  | 55.13  | 50.46|
| 64      | 58.79  | 33.38  | 77.47  | 59.68  | 53.00|
| 128     | 53.73  | 29.55  | 77.42  | 60.77  | 51.11|
| 256     | 48.35  | 24.39  | 73.36  | 54.23  | 47.89|

Table 7. Effect of the number of input frames.

| #Sentences | R1@0.5 | R1@0.7 | R5@0.5 | R5@0.7 | mIoU |
|------------|--------|--------|--------|--------|------|
| 2          | 33.86  | 17.31  | 70.41  | 44.00  | 38.73|
| 3          | 46.15  | 22.03  | 81.58  | 63.17  | 47.05|
| 4          | 58.79  | 33.38  | 77.47  | 59.68  | 53.00|
| 5          | 35.41  | 17.51  | 69.19  | 48.74  | 39.58|

Table 8. Effect of the number of input sentences.

| Vid | Txt | R1@0.5 | R1@0.7 | R5@0.5 | R5@0.7 | mIoU |
|-----|-----|--------|--------|--------|--------|------|
| ✓   | ✓   | 25.71  | 12.69  | 66.34  | 41.45  | 29.85|
| ✓   | ✓   | 22.86  | 10.75  | 63.95  | 40.83  | 30.11|
| ✓   | ✓   | 38.18  | 16.05  | 74.56  | 54.58  | 40.88|
| ✓   | ✓   | 58.79  | 33.38  | 77.47  | 59.68  | 53.00|

Table 9. Positional Encodings.

A.3. More Qualitative Results

To better see how VidGTR understands the video contexts, we provide additional qualitative examples and contrast the success and failure cases in Fig. 9. The results show that the VidGTR successfully identifies the object described in the query and accurately localize the timespan, even if multiple objects appear in the video (row 1&2). Moreover, VidGTR correctly reasons about the action that takes place from the first person point of view (row 3). Lastly, even if the same object appears repeatedly, VidGTR distinguishes subtle contextual differences between them well (row 4). However, VidGTR often fails to capture short-term events, especially when the object is too small (row 1&2). VidGTR suffers when the time the event takes place is too long (e.g., whole video length) (row 3). Also, VidGTR fails when the labeled timespan and the actual timespan where the query description matches the video content are significantly different (row 4).

| λL1:λiou:λsg | R1@0.5 | R1@0.7 | R5@0.5 | R5@0.7 | mIoU |
|--------------|--------|--------|--------|--------|------|
| 1:1:1        | 53.39  | 30.79  | 80.68  | 60.76  | 51.24|
| 2:1:1        | 56.42  | 31.59  | 78.90  | 63.03  | 52.77|
| 1:2:1        | 58.03  | 31.23  | 78.02  | 60.49  | 52.15|
| 1:1:2        | 57.41  | 32.91  | 77.09  | 57.49  | 53.50|
| 1:3:1        | 49.59  | 28.03  | 66.81  | 48.78  | 48.18|
| 1:3:2        | 58.79  | 33.38  | 77.47  | 59.68  | 53.00|

Table 6. Loss balancing parameters.
Figure 9. **Qualitative examples of success and failure cases** of ViDGTR on the ActivityCaptions dataset. The predicted timespan is considered correct only if it has sufficiently high IoU (i.e., IoU > 0.5) with ground truth timespan. Empty bars represent ground truths, and colored bars represent predictions.