Explore-And-Match: Bridging Proposal-Based and Proposal-Free With Transformer for Sentence Grounding in Videos

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Abstract

Natural Language Video Grounding (NLVG) aims to localize time segments in an untrimmed video according to sentence queries. In this work, we present a new paradigm named Explore-And-Match for NLVG that seamlessly unifies the strengths of two streams of NLVG methods: proposal-free and proposal-based; the former explores the search space to find time segments directly, and the latter matches the predefined time segments with ground truths. To achieve this, we formulate NLVG as a set prediction problem and design an end-to-end trainable Language Video Transformer (LVTR) that can enjoy two favorable properties, which are rich contextualization power and parallel decoding. We train LVTR with two losses. First, temporal localization loss allows time segments of all queries to regress targets (explore). Second, set guidance loss couples every query with their respective target (match). To our surprise, we found that training schedule shows divide-and-conquer-like pattern: time segments are first diversified regardless of the target, then coupled with each target, and fine-tuned to the target again. Moreover, LVTR is highly efficient and effective: it infers faster than previous baselines (by 2× or more) and sets competitive results on two NLVG benchmarks (ActivityCaptions and Charades-STA).

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 [10, 14, 32, 50, 51]. While text-video retrieval aims to match a trimmed video clip to the language query, NLVG aims to find accurate time segments 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 NLVG can be categorized into two families: 1) proposal-based methods [2, 6, 15, 16, 19, 27, 28, 35, 45, 47, 50, 52, 56, 58, 59, 60], which generate a bunch of proposals in advance and select the best match with target segments, and 2) proposal-free methods [4, 7, 8, 9, 17, 31, 33, 38, 44, 47, 54, 55, 57], which estimate start and end timestamps aligned to the given description directly. The proposal-based approaches generally show strong performance at the trade-off of the prohibitive cost of proposal generation. They contradict the end-to-end philosophy, and their performances are significantly influenced by hand-designed pre-processing or post-processing steps such as dense proposal generation [11, 49] or non-maximum suppression [41, 47, 53] 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 segment prediction is too large.

In this work, we present a new NLVG paradigm named Explore-And-Match that combines the strengths of the two mainstream approaches by formulating NLVG as a direct...
To solve NLVG as a set prediction problem, we design an approach with two previous approaches is shown in Fig. 2. Our Explore-And-Match paradigm unifies two methods and instead makes flexible time segment proposals. Our method starts with randomly initialized proposals, explores time space, and then matches the corresponding target. By design, our LVTR can predict multiple targets simultaneously, while earlier approaches could only predict single target at a time.

set prediction problem. Our method keeps the use of proposals while flexibly predicting time segments. Also, it avoids time-consuming pre-processing and post-processing via a direct set prediction. A conceptual comparison of our approach with two previous approaches is shown in Fig. 2. To solve NLVG as a set prediction problem, we design an end-to-end trainable model called LVTR based on the transformer encoder-decoder architecture [43]. The primary ingredients of LVTR are bipartite set matching and parallel decoding with a small set of learnable proposals 1. To train all learnable proposals in parallel, we adopt the Hungarian algorithm [23] 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, LVTR allows us to forgo the use of manually-designed components (e.g., temporal anchors, windows) that encode prior knowledge into the NLVG pipelines. Furthermore, learnable proposals can interact with visual-linguistic representations as well as themselves to directly output the final time segment predictions in a single run.

Under the Explore-And-Match scheme, the overall training schedule is governed by temporal localization loss and set guidance loss, where the temporal localization loss is responsible for generating accurate time segments, and set guidance loss is responsible for matching predictions with their respective targets (i.e., making target-specific predictions). To match the learnable proposals with their targets, we first divide the learnable proposals by the number of query sentences into several subsets, then set guidance loss progressively forces each subset of proposals to match its corresponding query. In the early stages of training, the temporal localization loss holds the major term in set matching than set guidance loss, which means that it is more of a priority for each subset to somehow approximate the time segment regardless of the target than to predict the corresponding target. Therefore, at first, random subsets learn to reduce temporal localization loss in a target-agnostic manner. Then, once the set guidance loss becomes more dominant than temporal localization loss, the subsets begin to predict each designated target. Finally, all learnable proposals learn to accurately align their respective target segments. learnable proposals diversify as they explore time space, and then match their respective targets. While the training LVTR under the Explore-And-Match scheme conforms to the end-to-end basis, it spontaneously divides and conquers the whole process rather than optimizing all the objectives simultaneously. We show the empirical evidence of the Explore-And-Match phenomenon (see Fig. 5) and confirm that this simple strategy is remarkably effective (see Fig. 1).

We evaluate LVTR trained under Explore-And-Match scheme on two challenging NLVG benchmarks — ActivityCaptions [3, 22] and Chrades-STA [15] — against the recent works. Our LVTR achieves new state-of-the-art results on two benchmarks, even without human priors such as knowledge of time segment distribution. Lastly, we confirm the effectiveness of our approach by conducting extensive ablation studies and analyses. To summarize, our contributions are three-fold:

- We present “Explore-And-Match”, a new NLVG paradigm that unifies the strengths of proposal-based and proposal-free methods by combining our new set guidance loss with temporal localization loss.
- We propose an end-to-end trainable model, LVTR, which models the NLVG as a set prediction problem. By design, our LVTR can predict multiple sentence queries at once. Moreover, this formulation stream-

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1We refer to trainable positional encodings as learnable proposals that are transformed into time segments by the transformer decoder.
lines the overall pipeline by removing the use of several heuristics.
• Comprehensive experiments and extensive ablation studies demonstrate the effectiveness of LVTR. Last but not least, LVTR establishes a new state-of-the-art on two NLVG benchmarks while accelerating inference time (by 2× or more) than previous methods.

2. Related Work

Video Grounding. The origin of NLVG traces back to the temporal activity localization [39], which attempts to locate the start and end timestamps of actions and identify its labels in an untrimmed video. Likewise, NLVG aims to retrieve the corresponding time segments, but it is grounded on language queries rather than a fixed set of action labels. Pioneering NLVG works [2, 15] define the task and provide benchmark datasets. Since then, numerous efforts have been made to push the boundaries of NLVG. Early works follow the proposal-based pipeline [2, 6, 15, 16, 19, 27, 28, 35, 45, 47, 50, 52, 56, 58, 59, 60], which segments a huge number of candidates at regular intervals on different scales, and then ranks them using an evaluation network. While proposal-based approaches provide reliable results, they are highly dependent on 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 is the proposal-free approaches [4, 7, 8, 9, 17, 31, 33, 38, 44, 47, 54, 55, 57], which tries to regress the time segments 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 tries to match the predefined proposals with ground truth, while the latter explores the whole space of time to find segment directly.

This work aims to integrate two streams of NLVG methods into a single paradigm named Explore-And-Match, by formulating NLVG as a direct set prediction problem. Our method generates flexible time segments 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 [43] is a 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 accounts for 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 [5], video instance segmentation [48], panoptic segmentation [46], human pose and mesh reconstruction [25], lane shape prediction [29], and human object interaction [61].

Among them, it is worth noting that the Detection Transformer (DETR) [5], the first transformer-based end-to-end object detector, achieved very competitive performance despite its simple design. DETR successfully removes many hand-crafted components from the object detection pipeline by using powerful relation modeling capabilities of transformer. The principal component of DETR is bipartite matching, notably the Hungarian algorithm [23], 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 NLVG model named Language Video Transformer (LVTR) based on the transformer architecture. The attention mechanism of the transformer allows every element of the input sequence to attend to each other while utilizing rich contextualization. This architectural strength makes the transformer particularly suitable for our NLVG formulation, a direct set matching problem. We note that final time segment predictions are directly generated in an end-to-end manner.

3. Preliminary: Transformer

Given that our model is built on the Transformer design, we will briefly discuss the general form of attention mechanisms, a key building block of Transformer. The common practice [43] is to use residual connections, dropout, and layer normalization. The attention mechanism is described in depth in [43].

Self-Attention. Self-Attention (SA) in the general qkv form is a popular yet strong mechanism for neural systems. We calculate a weighted sum over all values v for each element in an input sequence x ∈ RS×D. The attention weights Ai,j are calculated by comparing two elements of the sequence to their respective query qi and key kj representations.

\[ [q, k, v] = xW_{qkv} + p, \]  
\[ A = \text{softmax} \left( \frac{qk^T}{\sqrt{D_h}} \right), \]  
\[ \text{SA}(x) = Av, \]  
where \( W_{qkv} \in \mathbb{R}^{D \times D_h} \) and \( A \in \mathbb{R}^{S \times S} \) are learnable weights. Since the Transformer is inherently permutation-invariant w.r.t input sequence, we add positional encoding \( p \in \mathbb{R}^{S \times D} \) [12] to embedded sequence in practice.

Multi-Head Self-Attention. Multi-Head Self-Attention (MHSA) is a simple extension of self-attention in which several self-attentions, dubbed "heads", are executed in parallel followed by a projection of their concatenated outputs.
4. Method

We first define the NLVG task and propose our end-to-end trainable LVTR. Next, we describe our training losses and set matching strategy. Finally, we present Explore-And-Match, a novel paradigm that unifies proposal-based and proposal-free methods.

4.1. Problem Formulation

NLVG aims to localize a set of language-grounded time segments in an untrimmed video. Since NLVG does not have a fixed set of sentence classes, the conventional classification approach is not applicable (i.e., taxonomy-free). Therefore, the NLVG model should be able to infer the time segments 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 time segments:

\[
\{y_i\}_{i=1}^K = \{(t_i, \hat{q}_i)\}_{i=1}^K ,
\]

where \( t_i = (t_i^s, t_i^e) \in [0, 1] \) defines the start and end timestamp normalized by the video length (i.e., time segment), 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 Eq. (5)). However, this limits the abundant interactions of the transformer with parallel decoding. In order to account for beneficial semantic and temporal relationships between the time segments, we view NLVG 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 time segments:

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

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

4.2. LVTR Architecture

The overall pipeline of LVTR is illustrated in Fig. 3. LVTR contains three main components: 1) a feature extractor to obtain 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 segment predictions.

The overall design is similar to that of original transformer encoder-decoder [43]. First, the transformer encoder processes video-text features, which are extracted from the backbone, added with temporal positional encoding \(^2\) 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 time segments, and also used to measure the correspondence between proposals and text queries.

\(^2\)We use a fixed absolute encoding to represent the temporal positions.
Video-Text Transformer. An input video $V \in \mathbb{R}^{T_0 \times C_0 \times H_0 \times W_0}$ passes through the C3D [42] (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 [34] embeddings. A set of sentence representations $f_t \in \mathbb{R}^{K \times D}$ ($K \geq 1, D = 512$) is obtained via a 2-layer bi-LSTM [20], 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, LVTR is equipped with a conventional C3D+LSTM backbone, but it can be trained on top of any modern backbone (e.g., CLIP [36], ViT [13]).

Language Video Transformer. To begin, video and text features are obtained using their respective feature extractors. We concatenate video-text features and pass them into the transformer encoder. The transformer 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 accessing 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 time segment 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 the 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.

4.3. Explore-And-Match

Considering that video includes multiple events over various periods, we view NLVG as a set prediction problem. To solve a set prediction problem between predicted and ground truth time segments, we adopt a Hungarian matching algorithm [23]. We define our loss based on the set matching results. Several training ingredients condense into Explore-And-Match, a new paradigm that combines two streams of methods, proposal-based and proposal-free.

**NLVG as a set prediction.** We search for one-to-one matching between the prediction set $\{\hat{y}_i\}_{i=1}^N$ and the ground truth set $\{y_i\}_{i=1}^K$ that optimally assigns predicted time segments 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 $\sigma \in \mathcal{S}_N$ 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 Eq. (12).

**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 address this problem, we introduce a set guidance loss that forces each prediction to be associated with a particular language query. Given \( K \) input queries, \( N \) proposals are uniformly partitioned into \( K \) subsets. The proposals within the \( j \)th subset are trained to 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:

\[
\mathcal{L}_{sg}(q_i) = - \sum_i \log \hat{p}_{\sigma(i)}(q_i). \tag{8}
\]

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

**Temporal localization loss.** Our temporal localization loss is a linear combination of the \( \ell_1 \) loss and the generalized IoU (gIoU) loss [37]:

\[
\mathcal{L}_{loc}(t_i, \hat{t}_{\sigma(i)}) = \lambda_{L1} \mathcal{L}_{L1}(t_i, \hat{t}_{\sigma(i)}) + \lambda_{iou} \mathcal{L}_{iou}(t_i, \hat{t}_{\sigma(i)}), \tag{9}
\]

where \( t_i \) is the ground truth time segment and \( \hat{t}_{\sigma(i)} \) is the predicted time segment for the prediction with index \( \sigma(i) \). \( \lambda_{L1}, \lambda_{iou} \in \mathbb{R} \) 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 time segments, even if relative errors are similar, whereas gIoU loss is robust to varying scales.

\[
\mathcal{L}_{L1}(t_i, \hat{t}_{\sigma(i)}) = ||t^s_i - \hat{t}^s_{\sigma(i)}||_1 + ||t^e_i - \hat{t}^e_{\sigma(i)}||_1, \tag{10}
\]

\[
\mathcal{L}_{iou}(t_i, \hat{t}_{\sigma(i)}) = 1 - \frac{\min(t^s_i, \hat{t}^s_{\sigma(i)}) - \max(t^e_i, \hat{t}^e_{\sigma(i)})}{\max(t^s_i, \hat{t}^s_{\sigma(i)}) - \min(t^e_i, \hat{t}^e_{\sigma(i)})}, \tag{11}
\]

where \( t^s \) and \( t^e \) denote the start and end timestamp, respectively. If two time segments \( t_i \) and \( \hat{t}_{\sigma(i)} \) perfectly overlap, the loss becomes 0; if they do not overlap at all, the loss becomes greater than 1.

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

\[
\mathcal{L}_\text{match}(y_i, \hat{y}_{\sigma(i)}) = - \mathbb{1}_{\{q_i \neq \emptyset\}} \hat{p}_{\sigma(i)}(q_i) + \mathbb{1}_{\{q_i \neq \emptyset\}} \mathcal{L}_{loc}(t_i, \hat{t}_{\sigma(i)}), \tag{12}
\]

where \( \mathbb{1} \) 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:

\[
\mathcal{L}_{set}(y, \hat{y}) = \sum_{i=1}^{N} \left[ \lambda_{sg} \mathcal{L}_{sg}(q_i) + \mathbb{1}_{\{q_i \neq \emptyset\}} \mathcal{L}_{loc}(t_i, \hat{t}_{\sigma(i)}) \right], \tag{13}
\]
where \( \lambda_{sg} \) is a loss coefficient. Only the positives are optimized to predict the corresponding ground truth time segments.

**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 NLVG 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.

The combination of training ingredients condenses into a novel learning paradigm named Explore-And-Match. As shown in Fig. 5, the set guidance loss and the temporal 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. 5(a)), predicted time segments are almost a random initialization without order. Before the sharp drop of a set guidance loss (Phase II: Fig. 5(b)), a set of time segments aligns with a set of ground truths in a target-agnostic manner. Interestingly, as the set guidance loss decreases, the \( \ell_1 \) loss and glIOU loss re-bound slightly to re-organize predictions to be target-specific. When all losses converge (Phase III: Fig. 5(c)), time segments 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.

5. Experiments

We first describe our experimental settings. Next, we report our main results on two challenging benchmarks: ActivityCaptions [3, 22] and Charades-STA [15]. Lastly, we provide detailed ablation studies on the model variants and losses, and analyze how LVTR works with visualizations.

5.1. Experimental Setup

**Datasets.** 1) ActivityCaptions [3, 22] contains about 20K untrimmed videos with language descriptions and temporal annotations, which was originally developed for the task of dense video captioning [22]. Following the convention, we used \( val_1 \) for validation and \( val_2 \) for testing since the test annotations are not publicly released. We also followed the standard split [54]. 2) Charades-STA [15] is built on Charades [40] and contains 6,672 videos of daily indoors activities. Each video is about 30 seconds long on average. We employed 12,408 video-sentence pairs for train and 3,720 pairs for test.

**Evaluation metrics.** Following [31, 54], we adopted two standard evaluation metrics for NLVG: 1) \( "R_{\alpha}@\mu" \), which denotes the percentage of test samples that have at least one correct result in top-\( \alpha \) retrieved results, 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 entire testing samples to compare the overall performance.

**Technical details.** We trained LVTR using AdamW [30] with an initial learning rate of 1e-4 and weight decay of 1e-4 for a batch size of 16. We used a linear learning rate decay by a factor of 10. We considered Xavier initialization [18] to set the initial values of all transformer weights. We used 64 frames that are uniformly sampled from video with four sentences as an input. We resized every frame to 112 × 112. The number of learnable proposals is proportionally set to 10 times the number of input queries. For a fair evaluation with baselines, we extracted video representations with C3D [42] pretrained on Sports-1M [21], and for the language part, we initialized each word with GloVe embeddings [34] and obtained sentence representation via 2-layer bi-LSTM [20]. In training, we set our loss weight \( \lambda_{l_1} : \lambda_{iou} : \lambda_{sg} \) to 1 : 3 : 2. We also used an auxiliary decoding loss [1] in decoder layers to speed up the convergence. The initial proposals are filled with learnable weights [5].

5.2. Main Results

**Comparison with state-of-the-art approaches.** We compared LVTR against recently proposed NLVG methods, which can be largely categorized into three groups: 1) proposal-based: CTRL [15], TGN [6], 2D-TAN [59], CSM-GAN [27], MSA [58], 2) proposal-free: ABLR [54], DE-BUG [31], DRN [55], VSLNET [57], CPNET [24], and 3) etc: BPNet [49], CBLN [26]. LVTR with C3D backbone (LVTR-C3D) sets new state-of-the-arts on two benchmarks (see Tab. 1): ActivityCaptions [3, 22] and Charades-STA [15]. Especially for R1@0.5 metric on ActivityCaptions dataset, LVTR-C3D achieved about 10% performance gain compared to CBLN [26]. We further improved the performance of LVTR by using CLIP [36] as a backbone (LVTR-CLIP) where a massive amount of image-text pairs are pre-trained with contrastive learning. Even freezing the backbone in the training phase, we observed that CLIP significantly boosts the performance, implying that visual-linguistic domain alignment is important.
Table 1. Comparison with the state-of-the-arts on two benchmark datasets (in the order of ActivityCaptions and Charades-STA).

| Methods       | Venue         | ActivityCaptions      | Charades-STA       |
|---------------|---------------|-----------------------|-------------------|
|               |               | R1@0.5 R1@0.7 R5@0.5 R5@0.7 mIoU | R1@0.5 R1@0.7 R5@0.5 R5@0.7 mIoU |
| CTRL [15]     | ICCV2017      | - - - -               | 23.63 8.89 58.92 29.52 |
| TGN [6]       | EMNLP2018     | 27.93 - 44.20 - -     | - - - - - - - -    |
| 2D-TAN [59]   | AAAI2020      | 44.51 26.54 77.13 61.96 | 39.70 27.1 80.32 51.26 |
| CSMGAN [27]   | ACMMM2020     | 49.11 29.15 77.43 59.63 | - - - - - - - -    |
| MSA [58]      | CVPR2021      | 48.02 31.78 78.02 63.18 | - - - - - - - -    |

Table 2. Ablation results of the loss functions.

| Methods       | ActivityCaptions | Charades-STA       |
|---------------|-------------------|-------------------|
|               | R1@0.5 R1@0.7 R5@0.5 R5@0.7 mIoU | R1@0.5 R1@0.7 R5@0.5 R5@0.7 mIoU |
| L1 loss       | 24.30 9.60 24.69 9.75 26.9 |
| gIoU loss     | 41.42 18.25 72.55 54.90 41.25 |
| set guidance  | 50.15 27.90 72.32 55.50 48.01 |
| Lsg Ll1 Liou  | 58.79 33.38 77.47 59.68 53.00  | 49.11 26.59 88.50 55.99 47.13 |

Table 3. Choices for pred-query correspondence measure.

| Methods | R1@0.5 R1@0.7 R5@0.5 R5@0.7 mIoU |
|---------|-----------------|
| Sim     | 13.11 2.75 13.15 2.79 23.73 |
| Att     | 34.36 18.10 82.42 63.31 39.16 |
| Cos     | 58.79 33.38 77.47 59.68 53.00 |

Inference speed. We compared several methods in terms of inference speed required to localize a single sentence query in Fig. 1. Our LVTR takes an average of 10ms to process a language query on ActivityCaptions dataset. LVTR runs much faster than the previous NLVG methods, especially 2× faster than DEBUG [31]. Furthermore, our set matching formulation eliminates the time-consuming preprocessing or post-processing stage, such as dense proposal generation and non-maximum suppression.

5.3. Analysis

Training with Explore-And-Match scheme. In Fig. 6, we investigated the behavior of LVTR during training under the Explore-And-Match scheme. Beginning with the random initialization, the proposals start to generate some variations in their predictions (1st). Thereafter, they become a state in which they can adapt to any time segment by slightly overlapping the boundaries of two ground truths (2nd). Then, each of their identities is determined, and their time segments are adjusted accordingly (3rd). After matching the identity, the proposals properly fit the relevant time segment in a fine-grained manner (4th). To our surprise, despite all training losses are given at once, the training process follows the form of a divide-and-conquer-like approach. We hypothesize that a carefully designed training scheme facilitates this systematic behavior.

Loss ablations. We analyzed the impact of the loss terms in Tab. 2: \( \ell_1 \) loss (\( \mathcal{L}_{l1} \)), gIoU loss (\( \mathcal{L}_{iou} \)), and set guidance loss (\( \mathcal{L}_{sg} \)). Since matching the target query is essential, we always used set guidance loss for all cases. When both \( \ell_1 \) and gIoU are disabled, the predictions are collapsed; thus, R1@0.5 and R5@0.5 showed almost the same results.

When either \( \ell_1 \) loss or gIoU loss is disabled, performance suffered significantly, implying that they are both required for accurate temporal localization. As using all three losses yielded the best result, we confirmed that two sub-losses of temporal localization loss (\( \ell_1 \) and gIoU) operate complementarily with absolute or relative criteria for time segment prediction.

Correspondence measures. We compared the various measures to calculate the correspondence between prediction and query in Tab. 3, which is then used in set guidance loss. In practice, we considered proposal-target matching using decoder output and the textual part of encoder output. The encoder-decoder attention weight (Att) is an intuitive way of determining which part of the encoder output each proposal corresponds to. Since it has direct ac-
Video

Language queries

GT

Time segment predictions

Query 1: Three scuba divers are ... camera panning all around the ocean.
Query 2: Several shots ... taking off their mask and waving to the camera.
Query 3: In the end the divers come to the surface.

Figure 6. Visualization of time segment predictions throughout training under Explore-And-Match scheme. The four predictions are in time order from top to bottom, where the first two of them show the explore process and the last two show the match process. The brighter the color, the more time segments predicted by proposals overlap.

| #enc | #dec | R1@0.5 | R1@0.7 | R5@0.5 | R5@0.7 | mIoU |
|------|------|--------|--------|--------|--------|------|
| 1    | 1    | 48.16  | 25.55  | 79.38  | 64.34  | 48.02|
| 2    | 1    | 48.20  | 26.08  | 77.57  | 64.05  | 47.67|
| 1    | 2    | 48.30  | 25.40  | 75.39  | 57.72  | 47.97|
| 2    | 2    | 55.22  | 31.13  | 76.39  | 61.65  | 50.99|
| 3    | 3    | 53.32  | 26.62  | 74.65  | 58.44  | 48.92|
| 4    | 4    | 58.79  | 33.38  | 77.47  | 59.68  | 53.00|
| 5    | 5    | 56.11  | 33.82  | 79.15  | 60.70  | 52.04|

Table 5. Model variants w.r.t encoder-decoder size.

| #proposals | R1@0.5 | R1@0.7 | R5@0.5 | R5@0.7 | mIoU |
|------------|--------|--------|--------|--------|------|
| 5          | 48.74  | 25.40  | 86.37  | 70.68  | 48.03|
| 10         | 58.79  | 33.38  | 77.47  | 59.68  | 53.00|
| 15         | 34.26  | 16.17  | 65.59  | 47.35  | 39.74|
| 20         | 6.64   | 2.16   | 18.02  | 6.11   | 13.07|

Table 6. Number of learnable proposals per query.

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 can no longer utilize temporally coordinated video contexts. Also, the temporal clue provided by textual positional encoding is significant in textual input since it aids in organizing the order of events. We used both positional encodings since both positional encoding largely contributes to the performance. To align the video and text in a different time axis, we employed separate positional encodings for each modality input.

Model size. To examine the effect of model size, we varied the number of encoder-decoder layers (see Tab. 5). We first compared 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 the 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 predictions among the candidates. However, considering that the performance degraded in 5-5, 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 searched for the optimal number of proposals per language query in Tab. 6. A small number of proposals limits sufficient interactions between positives and negatives, resulting in sub-optimal performance, whereas an excessive quantity of proposals re-

| 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 4. Positional Encodings.

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 can no longer utilize temporally coordinated video contexts. Also, the temporal clue provided by textual positional encoding is significant in textual input since it aids in organizing the order of events. We used both positional encodings since both positional encoding largely contributes to the performance. To align the video and text in a different time axis, we employed separate positional encodings for each modality input.

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Figure 7. **NLVG results (middle) of LVTR with proposal-video attention map (bottom).** The bottom color map indicates the attention to the video time segment (column) of each proposal (row), where the brighter the color, the higher attention is. Note that each subset of learnable proposals attends to the corresponding video contexts to predict the target time segments.

Figure 8. **Visualization of predicted time segments** on Activity-Captions for 10 out of all learnable proposals. Each prediction is represented by a colored point on the horizontal (center) and vertical (width) axes, where the color indicates the width. We observe that each learnable proposal learns to specialize on certain time zones and durations.

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.

**Attention visualization on qualitative example.** In Fig. 7, we show a sample NLVG result, where the bars lie along the time axis represent the time segments grounded on the query. The predictions (color bars) generated by LVTR nearly matched the target time segments (empty bars). As shown in the proposal-video attention map (bottom), the time segments in which each subset of learnable proposals attend to are mostly overlapped with their corresponding time segment prediction; for example, the third subset attend to the end part of the video. This implies that proposals within the same subset consider similar parts of the video contexts when predicting the target query.

| \( \lambda_{L1}:\lambda_{iou}:\lambda_{sg} \) | 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 | 56.62 | 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 7. Loss balancing parameters.**

| #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 8. 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 | 54.05 |
| 4 | **58.79** | **33.38** | 77.47 | 59.68 | **53.00** |
| 5 | 35.41 | 17.51 | 69.19 | 48.74 | 39.58 |

**Table 9. Effect of the number of input sentences.**

**Distribution of learnable proposals.** We visualize the time segment predictions of 10 out of all learnable proposals in Fig. 8. We observed that they exhibited a variety of distinct patterns, implying that LVTR learns unique specializations for each proposal. More specifically, each proposal includes several operating modes attending to different time zones and durations. For example, the top-third proposal learned about a long period of time at the beginning of the videos. Overall, all proposals have a mode that predicts video-wide durations, denoted by the color blue.

**Loss hyperparameters.** We searched for optimal loss hyperparameters in Tab. 7. We began 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 yielded 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 Tab. 8 and Tab. 9, 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 guarantee 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.

5.4. Qualitative Results

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

6. Discussion

Our framework inherits the popular DETR [5] framework that is for object detection, making it easy for practitioners to implement, yet we show that our framework can effectively solve the NLVG problem with little modifications. The reason for using the DETR framework is that if object detection is a problem of finding bounding boxes on the spatial axis, NLVG is a problem of finding bounding boxes on the temporal axis.

We designed the NLVG problem as a set prediction problem, which allowed us to integrate explore and match into a single step. For set prediction, we use learnable proposals, which should be able to generate flexible proposals as in proposal-free, while resolving the largest issue of proposal-based methods: redundant pre-generated proposals. To this end, the ideal method for learning the learnable proposals is to use the property of the Transformer, which models the pairwise interaction between all tokens in the input sequence. As we input the learnable proposals as a sequence to the Transformer decoder, each learnable proposal adjusts the time segments in consideration of other learnable proposals such that they are neither biased nor overlapped (as shown in Fig. 8).

Unlike typical NLVG methods, our framework can handle multiple queries (of course single query too) — our language encoder processes sentence units rather than word units, making multi-query learning possible. With a fixed number of learnable proposals, our method can simultaneously predict multiple answers. This is effective in that learnable proposals can utilize the temporal order between sentences, and it is efficient in that learnable proposals can predict multiple sentences at the same time (see the results in Fig. 1). Our newly introduced set guidance loss matches the learnable proposals with multiple queries. The set guidance loss divides the full set of learnable proposals into several subsets according to the number of input queries and induces each subset to be learned according to each query. Combining the set guidance loss with temporal localization loss, our framework falls into the Explore-And-Match scheme — every learnable proposal first explores the search space, and then accurately matches the target. Surprisingly, since our network is learned end-to-end, optimization for both losses occurs simultaneously, yet we can observe that all learnable proposals divide-and-conquer the problem (explore first and match next) holistically and systematically (see Fig. 5 and Fig. 6).

7. Conclusion

We have introduced Explore-And-Match, a new NLVG paradigm that unifies proposal-based and proposal-free approaches; our approach inherits the former concept while proposals are flexible as in the latter. We viewed NLVG as a direct set prediction problem, and designed a transformer-based LVTR to solve this problem. LVTR is end-to-end trainable and can predict time segments in parallel by utilizing abundant video-text contexts. We employed bipartite matching in tandem with two key losses: 1) set guidance loss forces to match the target, and 2) temporal localization loss regresses each proposal to fit the corresponding time segment. Our approach diversifies proposals in the explore stage, and aligns each learnable proposal with specific target in the match stage. LVTR achieved new state-of-the-art results on two challenging benchmarks (ActivityCaptions and Charades-STA) while doubling the inference speed. We hope our exploration and findings facilitate future research on NLVG.
Figure 9. Qualitative examples of success and failure cases of LVTR on the ActivityCaptions dataset. The predicted time segment is considered correct only if it has sufficiently high IoU (i.e., IoU > 0.5) with ground truth time segment. Empty bars represent ground truths, and colored bars represent predictions.

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