Seq2Time: Sequential Knowledge Transfer for Video LLM Temporal Grounding

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Abstract

Temporal awareness is essential for video large language models (LLMs) to understand and reason about events within long videos, enabling applications like dense video captioning and temporal video grounding in a unified system. However, the scarcity of long videos with detailed captions and precise temporal annotations limits their temporal awareness. In this paper, we propose ***Seq2Time****, a data-oriented training paradigm that leverages sequences of images and short video clips to enhance temporal awareness in long videos. By converting sequence positions into temporal annotations, we transform large-scale image and clip captioning datasets into sequences that mimic the temporal structure of long videos, enabling self-supervised training with abundant time-sensitive data. To enable sequence-to-time knowledge transfer, we introduce a novel time representation that unifies positional information across image sequences, clip sequences, and long videos. Experiments demonstrate the effectiveness of our method, achieving a 27.6% improvement in F1 score and 44.8% in CIDEr on the YouCook2 benchmark and a 14.7% increase in recall on the Charades-STA benchmark compared to the baseline.*

1. Introduction

Developing versatile video large language models (LLMs) capable of perceiving temporal dynamics in long-term videos is crucial for advancing toward artificial general intelligence and has numerous impactful real-world applications, *e.g.*, enabling intelligent surveillance systems to detect anomalous activities, assisting in medical diagnostics through the analysis of patient behavior, and facilitating advanced sports analytics by recognizing patterns and strategies over entire games.

Building upon well-trained LLMs [2, 7, 8, 14, 39], visual instruction tuning [24]—which projects visual representations into the language embedding space—has significantly advanced the ability to perform various multimodal tasks, such as image captioning [18, 23, 42], video question answering [6, 19, 20, 26, 37], and 3D perception [11, 17, 31]. The success of multimodal LLMs (MLLMs) in general vision-language tasks has further inspired the development of time-sensitive MLLMs [10, 12, 13, 29, 30, 34] for long-term video understanding, such as dense video captioning [15] and temporal video grounding [1, 9].

Creating time-sensitive instruction tuning data from existing video datasets with timestamp annotations [1, 9, 15, 32, 40] is essential for temporal grounding. However, current time-related video datasets face significant limitations. First, they are limited in scale due to the labor-intensive process of timestamp annotation; datasets like TimeIT [30] and VTG-IT [10] contain only around 125K and 120K videos respectively, which is substantially fewer than general video instruction tuning datasets without detailed time annotation, *e.g.*, VideoChat2 [20] includes over 800K videos. However, the number of training data is crucial in time-sensitive MLLM training. As illustrated in Table 1, when randomly removing 12% task-irrelevant training data for TimeChat [30], the average performance of dense video captioning on YouCook2 could drop 13.4%; while intentionally removing task-relevant training data (*e.g.*, dense video captioning), the performance sharply degrades 65.5%. Second, the captions in these datasets often lack richness and precision; the visual-language alignment is less accurate compared to high-quality datasets. For example, LLaVA-Instruct-150K [24] provides detailed image captions and specifies key object locations, greatly enhanc-

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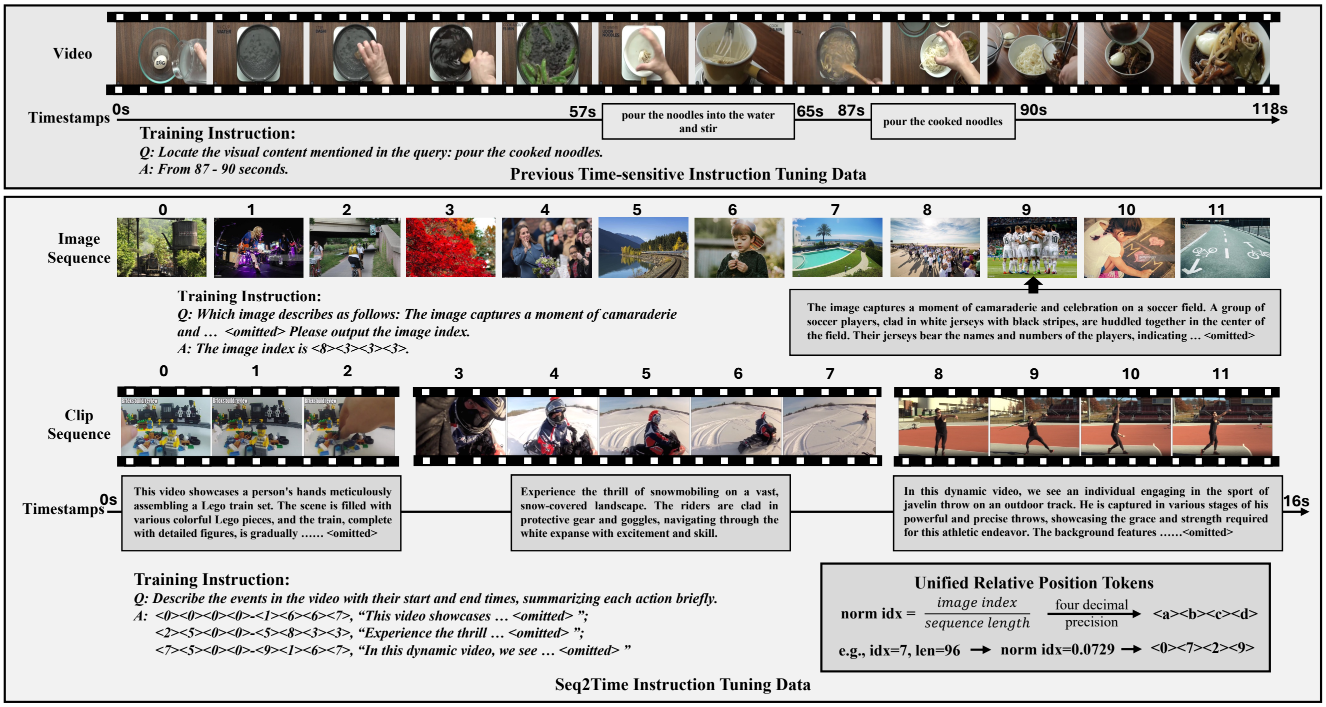


Training Instruction:

Q: Locate the visual content mentioned in the query: pour the cooked noodles.

A: From 87 - 90 seconds.

Previous Time-sensitive Instruction Tuning Data

Training Instruction:

Q: Which image describes as follows: The image captures a moment of camaraderie and … <omitted> Please output the image index.

A: The image index is <8><3><3><3>.

The image captures a moment of camaraderie and celebration on a soccer field. A group of soccer players, clad in white jerseys with black stripes, are huddled together in the center of the field. Their jerseys bear the names and numbers of the players, indicating … <omitted>

This video showcases a person's hands meticulously assembling a Lego train set. The scene is filled with various colorful Lego pieces, and the train, complete with detailed figures, is gradually …… <omitted>

Experience the thrill of snowmobiling on a vast, snow-covered landscape. The riders are clad in protective gear and goggles, navigating through the white expanse with excitement and skill.

In this dynamic video, we see an individual engaging in the sport of javelin throw on an outdoor track. He is captured in various stages of his powerful and precise throws, showcasing the grace and strength required for this athletic endeavor. The background features ……<omitted>

Training Instruction:

Q: Describe the events in the video with their start and end times, summarizing each action briefly.

A: <0><0><0><0>-<1><6><6><7>, "This video showcases … <omitted> ";
<2><5><0><0>-<5><8><3><3>, "Experience the thrill … <omitted> ";
<7><5><0><0>-<9><1><6><7>, "In this dynamic video, we see … <omitted> "

$$\text{norm idx} = \frac{\textit{image index}}{\textit{sequence length}} \xrightarrow[\text{precision}]{\text{four decimal}} \text{<a><b><c><d>}$$

e.g., idx=7, len=96 → norm idx=0.0729 → <0><7><2><9>

Seq2Time Instruction Tuning Data

Figure 1. Illustration of our proposed Seq2Time. While existing approaches [10, 30] rely on timestamp-annotated long videos, Seq2Time leverages image and short video datasets. We introduce a novel time representation of **unified relative position token** that bridges different sequence types by encoding positions as 4-digit codes—each digit becomes a learnable embedding in the language space, enabling seamless knowledge transfer in the LLM embedding space.

ing perception during instruction following. These limitations—the constrained dataset sizes and suboptimal caption quality—not only hinder the training of temporally aware video LLMs but also impede their performance in understanding and reasoning over long-term videos.

To address these challenges, we propose **Seq2Time**, a data-oriented training paradigm that leverages sequences of independent images and short video clips to enhance temporal grounding in long videos. Our intuition is that MLLMs do not inherently "perceive time" but recognize the correspondence between visual content and its position in a sequence. Therefore, we construct two types of data: i) image sequence data and ii) short video clip sequence data. For the image sequence data (IS), based on correlations between image captions and their indices in the sequence, we design three sophisticated pretext tasks: a) image index grounding, b) indexed image captioning and c) adjacent location reasoning, enforcing the MLLM to link the sequential location of a specific image to its textual content and vice versa. For the clip sequence data (CS), we first generate captions using LongVA [38] given the video and its action labels; then, we combine several short clips along with their sequential positions to form a long video. Similarly, the model is trained to learn the correspondence between the captions of the short clips and their sequential positions. Due to the large scale of image [16] and short video clip [4] datasets, we can easily sample a vast number of long sequences with high-quality caption annotations, significantly improving the quality and quantity of the instruction tuning training data.

It is worth noting that the image sequence data and clip sequence data in Seq2Time offer distinct advantages. The three pretext tasks associated with image sequences are more challenging than the two downstream tasks, as they require locating one or few specific images within a long sequence. Additionally, the quality of image captions is generally higher than that of video data. On the other hand, the clip sequence data aligns more closely with real-world long video sequences, both in terms of data characteristics and training objectives. Overall, the two types of data are complementary in our Seq2Time.

Importantly, to facilitate seamless knowledge transfer from image and clip sequence to temporal understanding in real real-world settings, we introduce a novel time representation called the *unified relative position token*. This representation unifies positional information across image sequences, clip sequences, and long videos within the LLM embedding space. By encoding the relative positions of images or clips as tokens, we enable the model to generalize the concept of position in a sequence to temporal locations in videos. This unification allows the video LLMs to inter-

Training Data	**SODA_c**	**CIDEr**	**Meteor**	**F1**
Full	1.0	2.9	1.1	12.7
w/o irr	1.2	2.0	0.8	10.5
w/o dvc	0.4	0.9	0.3	4.8

Table 1. Impact of data loss on the performance of TimeChat on dense video captioning (YouCook2). We compare the full training data results and 12% less training data. “irr” means task-irrelevant data, and “dvc” means dense video captioning data. The average performance drops 13.4% and 65.5%, respectively.

pret positional cues consistently across different modalities, effectively bridging the gap between artificial sequences and continuous video content. Our contributions are summarized as follows:

- We propose **Seq2Time**, a novel data-oriented training paradigm that enhances temporal understanding in video LLMs through image and clip sequences, enabling effective temporal grounding in long videos without requiring extensive timestamp annotations.
- We introduce three well-designed pretext tasks for image sequence data (image index grounding, indexed image captioning, and adjacent location reasoning) that effectively enhance MLLMs’ ability to locate and describe temporal events in sequences.
- We develop a unified relative position token representation that bridges image indices and video timestamps in the LLM embedding space, facilitating efficient knowledge transfer between different sequence types and temporal understanding tasks.
- Experiments validate the effectiveness of Seq2Time, achieving significant improvements over the baseline model: 44.8% gain in CIDEr and 27.6% in F1 score on YouCook2, and 17.1% improvement in R@1 (IoU=0.7) on Charades-STA.

2. Related Work

2.1. Visual Instruction Tuning Data

The emergence of multimodal LLMs [6, 19, 24, 26, 42] has revolutionized vision-language understanding, largely due to advances in visual instruction tuning [24] and carefully curated instruction datasets [5, 17, 19, 24]. A significant milestone was established in [24], where they introduced a standardized protocol using GPT-4 [28] to transform COCO dataset [22] annotations into LLM-compatible instruction data. This approach was later extended to video understanding, with [19] leveraging WebVid-10M [3] to create comprehensive video-centric instruction tuning datasets.

Several efforts have been made to create time-sensitive instruction-tuning datasets. LITA [13] developed specialized instruction data for temporal localization. TimeIT [30] focused on dense video captioning and grounding. However, these time-sensitive datasets, particularly TimeIT, face limitations in both scale and quality due to the resource-intensive nature of timestamp annotation. Our work addresses these challenges by introducing a novel approach that leverages images and short clips to create rich instruction tuning data, as illustrated in Figure 1, ultimately enhancing video LLMs’ temporal understanding capabilities.

2.2. Time-sensitive MLLMs

Recent works have made significant strides in developing time-sensitive MLLMs through architectural innovations. TimeChat [30] introduces a dual Q-Former approach: one for timestamp embedding through cross-modal attention and another utilizing sliding windows for long video sequences. VTimeLLM [12] employs a three-stage pipeline that progressively learns visual-text alignment, event boundaries, and timestamp perception. Momentor [29] emphasizes the significance of temporal representation and segment-level modeling, while HawkEye [34] utilizes coarse-grained clip descriptions as intermediate representations with recursive temporal grounding. VTG-LLM [10] introduces absolute-time tokens to minimize quantization errors in time perception, alongside slot-based token compression to address context length limitations. Grounded-VideoLLM [33] combines relative time tokens with a two-stream visual encoding architecture for improved temporal understanding. While these approaches focus on architectural innovations, our work takes a fundamentally different approach by investigating the potential of **sequence learning from images and short clips**. We address the critical challenge of insufficient timestamp annotations in long video datasets by exploring, for the first time, how sequential knowledge can be effectively transferred to enhance temporal understanding in long videos.

2.3. Time-aware Video Understanding

Dense video captioning [15] and temporal video grounding [1, 9] represent tasks in video understanding that require precise temporal comprehension. Recent advances in dense video captioning have explored various innovative approaches: Zhu et al. [43] developed an end-to-end framework that integrates ASR signals with simultaneous timestamp and caption prediction, while Yang et al. [36] introduced a specialized token-based temporal framework trained on large-scale data. To enhance efficiency and modularity, Zhu et al. [41] proposed a clustering-based memory bank that can be readily integrated into existing architectures. While unified frameworks [21, 35] have emerged to handle multiple temporal understanding tasks simultaneously, these approaches are typically designed for specific video understanding tasks with dedicated architectures. In contrast, our work focuses on enhancing Video LLMs’ temporal understanding capabilities while preserving their general-purpose reasoning abilities, enabling a more versatile and comprehensive solution for video understanding.

3. Seq2Time

Traditional approaches to training time-sensitive video LLMs have been constrained by the limited availability of temporal annotations in long video datasets. To address this challenge, we propose Seq2Time, a novel paradigm that leverages abundant image and short video data to create rich sequential training data with self-constructed temporal information. Our approach consists of three components: image sequence data (Section 3.1) that exploits index-caption correspondence in long sequences, clip sequence data (Section 3.2) that utilizes LongVA [38] to generate high-quality captions for short video clips, and a unified relative position token (Section 3.3) that bridges different types of sequential data in the LLM embedding space.

3.1. Image Sequence Data

We utilize three LLaVA-ReCap datasets [16] (COCO118K, BLIP558K, and CC3M) as our data source due to their rich textual content and consistent image-text alignment. To adapt the image data for downstream time-aware video understanding tasks, we design three pretext tasks: Image Index Grounding, Indexed Image Captioning, and Adjacent Location Reasoning, as shown in Figure 2, aimed at enhancing sequence localization abilities in Video LLMs.

Image Index Grounding (IIG) trains the model to locate specific images within a sequence based on their descriptions. Given one or several captions, the model must identify the corresponding image index or indices, mimicking temporal grounding in videos. The input format is: *Which image matches the description: <CAPTION>? Please output the image index*, with output: *The image index is <INDEX>.*

Indexed Image Captioning (IIC) reverses this process by requiring the model to generate descriptions for specific indexed images, analogous to dense video captioning. A typical input is: *Please describe the image with index <INDEX>*, with output: *The image with index <INDEX> describes <CAPTION>.*

Adjacent Location Reasoning (ALR) challenges the model to understand sequential relationships by identifying and describing neighboring images. The task takes input: *What is the image right before/after the image described as <CAPTION1>? Please provide the index and describe this image*, and expect output: *The image index is <INDEX>. It describes <CAPTION2>.* By combining both index grounding and image description in a sequential context, this task strengthens the model's ability to perform both temporal localization and content understanding, which are essential for video understanding tasks like dense captioning and temporal grounding.

In our implementation, we limit the maximum number of target images to 5 for both IIG and IIC tasks, with 10 different template variations for questions and answers (detailed templates can be found in **Appendix A**). Each training sequence consists of 96 randomly sampled images, from which up to 5 are selected as targets for caption-based prompts. From our source datasets containing about 3.7M images, we randomly sample 300K training instances, evenly distributed across the three pretext tasks (100K each). This approach not only ensures rich textual descriptions to enhance text generation capabilities but also strengthens sequence localization abilities through our carefully designed pretext tasks.

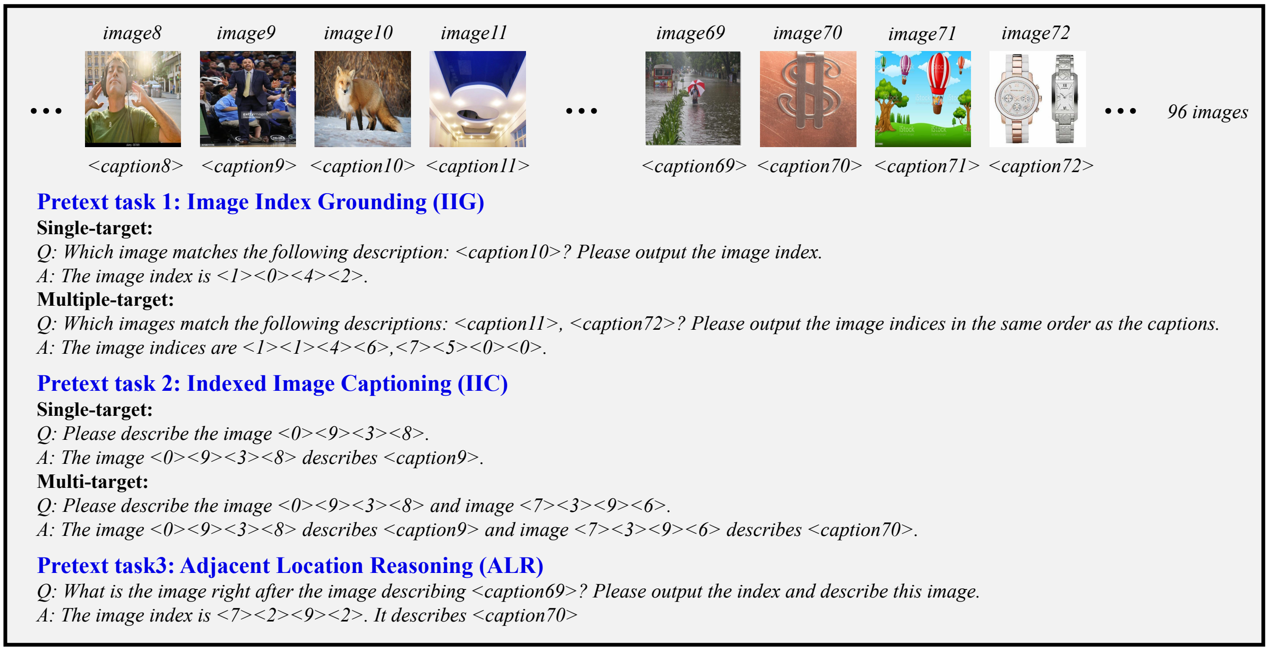
3.2. Clip Sequence Data

To better simulate real long videos with multiple events, we utilize the Kinetics-700 [4] dataset to construct clip sequence data. We employ LongVA [38] to generate detailed descriptions for each clip, conditioning on the action labels to ensure high-quality captions. The captioned clips are then combined to create longer sequences, which serve as training data for both dense video captioning and temporal video grounding tasks. To create diverse temporal structures, we randomly sample between 2 to 10 clips per sequence, mimicking multi-event scenarios in long videos. While most Kinetics-700 clips are 10 seconds long, we intentionally avoid uniform temporal spacing by applying varying frame rates during sampling. This strategy, illustrated in Figure 3, ensures that our model learns to handle non-trivial temporal relationships and variable-length segments within sequences.

3.3. Unified Relative Position Tokens

Previous works have represented time in video LLMs using either free-form language (*e.g.*, "2.05 seconds") [30] or special learnable tokens (*e.g.*, <T_TWO><T_DOT><T_ZERO><T_FIVE>) [10]. However, learning absolute time is often suboptimal for two reasons: 1) videos may have different frame rates, making absolute time less meaningful across datasets, and 2) the primary goal is to capture the correspondence between visual content and its relative sequential position. Furthermore, to enable effective sequence-to-time knowledge transfer, we need to bridge the semantic gap between image indices and video timestamps through a unified representation.

We propose using relative position tokens that work seamlessly across both image sequences and video data (Figures 2 and fig:clipseq). Instead of using direct indices which could lead to complex token sequences (*e.g.*, <1><2>...<99>...), we normalize each position (*i.e.*, image or frame index) to a 4-digit decimal representation: $I_{\text{norm}} = \text{round}\left(\frac{i}{L}, 4\right)$, with i the image (or frame) index and L the sequence length. For example, in a 96-image se-



Pretext task 1: Image Index Grounding (IIG)

Single-target:

Q: Which image matches the following description: <caption10>? Please output the image index.

A: The image index is <1><0><4><2>.

Multiple-target:

Q: Which images match the following descriptions: <caption11>, <caption72>? Please output the image indices in the same order as the captions.

A: The image indices are <1><1><4><6>,<7><5><0><0>.

Pretext task 2: Indexed Image Captioning (IIC)

Single-target:

Q: Please describe the image <0><9><3><8>.

A: The image <0><9><3><8> describes <caption9>.

Multi-target:

Q: Please describe the image <0><9><3><8> and image <7><3><9><6>.

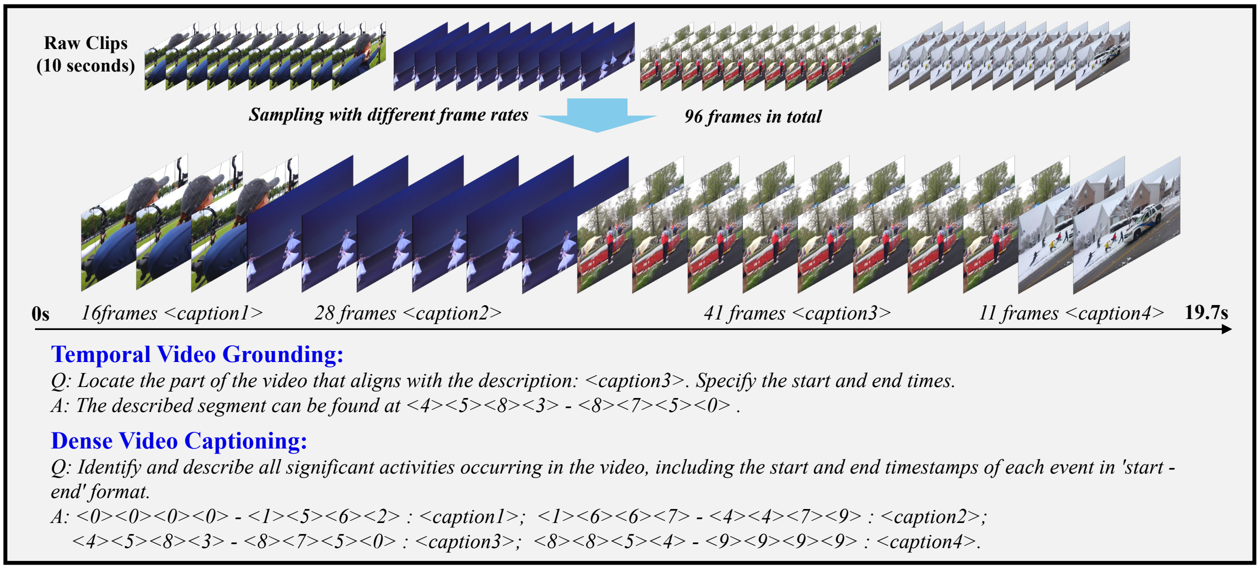
A: The image <0><9><3><8> describes <caption9> and image <7><3><9><6> describes <caption70>.

Pretext task3: Adjacent Location Reasoning (ALR)

Q: What is the image right after the image describing <caption69>? Please output the index and describe this image.

A: The image index is <7><2><9><2>. It describes <caption70>

Figure 2. Image sequence data in Seq2Time, featuring three complementary pretext tasks designed to leverage index-caption correspondence. IIG (Image Index Grounding) mimics temporal grounding through position prediction, IIC (Indexed Image Captioning) parallels dense video captioning, and ALR (Adjacent Location Reasoning) enhances sequential understanding through neighbor relationships.



Temporal Video Grounding:

Q: Locate the part of the video that aligns with the description: <caption3>. Specify the start and end times.

A: The described segment can be found at <4><5><8><3> - <8><7><5><0> .

Dense Video Captioning:

Q: Identify and describe all significant activities occurring in the video, including the start and end timestamps of each event in 'start - end' format.

A: <0><0><0><0> - <1><5><6><2> : <caption1>; <1><6><6><7> - <4><4><7><9> : <caption2>;
<4><5><8><3> - <8><7><5><0> : <caption3>; <8><8><5><4> - <9><9><9><9> : <caption4>.

Figure 3. Clip sequence data in Seq2Time. We use LongVA to generate captions for short video clips from Kinetics-700, then combine multiple clips from different action categories to simulate longer videos. Temporal annotations are derived from sequence positions of clips. The resulting sequences serve as training data for both temporal grounding and dense video captioning tasks.

quence, the 7th image's normalized index would be 0.0729, encoded as `<0><7><2><9>` (Figure 1). The 4-digit precision is carefully chosen to balance accuracy and complexity. For a typical 1-minute video at 30 fps sampled at 96 frames, this representation achieves an average temporal error of just 0.13%. More specifically, each digit serves a different purpose: the first digit represents the coarse position, while subsequent digits provide increasingly fine-grained localization within that section. This hierarchical structure helps the model learn temporal relationships at different scales.

Our approach introduces only 10 new tokens (`<0>` through `<9>`) to the LLM vocabulary, making it highly efficient for training while providing a unified representation that bridges image sequences and video timestamps in the LLM embedding space. During inference, absolute timestamps can be easily reconstructed from these relative positions using the video frame rate, enabling precise temporal localization without the need for learning video-specific timing patterns.

4. Experiments

4.1. Experiment Setup

Training Data Our training dataset comprises three main components: 1) Seq2Time instruction data, consisting of 300K image sequence instances and 100K clip sequence instances; 2) 110K temporal understanding samples from TimeIT [30]; and 3) general video caption data, including 40K instances from Valley [25] and 93K from ShareGPT4Video [5]. For Seq2Time data, we employ balanced sampling across tasks: the image sequence tasks (IIG, IIC, and ALR) are randomly selected with equal probability; and similarly, the clip sequence tasks (dense video captioning and temporal video grounding) are sampled uniformly.

Implementation Details We evaluate Seq2Time using TimeChat [30] as our baseline model. The training process consists of two phases: initial training for 1 epoch with the complete dataset, followed by 3 epochs of fine-tuning using only TimeIT and Valley (40K) data. Training parameters include a LoRA rank of 32, batch size of 8, and 96 sampled frames per video, following TimeChat's configuration. All experiments are conducted on 8 A100 GPUs (80GB each). For evaluation, we follow TimeChat's metrics: dense video captioning is assessed using *SODA_c*, *CIDEr*, and *Meteor* for text quality, and *F1 score* for temporal accuracy. Temporal video grounding is evaluated using *R@1* with IoU thresholds of 0.5 and 0.7. Note that our reproduced baseline results are slightly lower than those reported in [30] due to partial Valley [25] data availability.

4.2. Main Results

We evaluate Seq2Time on two standard benchmarks for temporal understanding: YouCook2 for dense video captioning and Charades-STA for temporal video grounding (Table 2). Our approach demonstrates consistent improvements across all metrics compared to the TimeChat baseline, even without the unified relative position token (RPT). The improvements are particularly notable in YouCook2's CIDEr and F1 scores, and Charades-STA's R@1(IoU=0.5), validating that our sequence-based training effectively enhances temporal understanding capabilities.

The addition of RPT further boosts performance, yielding significant improvements: +30% in SODA_c and +27.6% in F1 score on YouCook2, and +17.1% in R@1(IoU=0.7) on Charades-STA. Notably, while TimeChat relies on approximately 120K manually annotated temporal samples, Seq2Time achieves superior performance using largely self-supervised data, leveraging the natural sequential correspondence between images/clips and their captions. We provide detailed ablation studies of individual components in the following section.

4.3. Dataset Effect

To analyze how different data components influence temporal understanding in video LLMs, we conduct comprehensive ablation studies on TimeChat, as shown in Table 3. Removing clip sequence (CS) data leads to performance drops in both dense video captioning and temporal grounding tasks, demonstrating its importance in the training pipeline.

Interestingly, incorporating additional video captions (MC) from ShareGPT4video [5] shows unexpected effects: while it doesn't significantly improve captioning quality, it substantially enhances temporal perception, yielding a 19.5% improvement in YouCook2's F1 score and 7.3% in Charades-STA's R@1(IoU=0.5). We hypothesize that exposure to more captions improves the model's ability to understand long-form video content, leading to better event boundary detection. The impact of image sequence data (IS) is particularly striking, especially in text generation quality. The CIDEr score shows a remarkable 48.3% improvement over the baseline, providing strong evidence that temporal understanding can be effectively learned from static image sequences. Notably, while the addition of MC and CS improves temporal localization, it results in a slight degradation in text generation quality. This may be because image sequence data inherently provides stronger sequential visual-language alignment (*i.e.* per-image captions), whereas video caption data represents visual-language correspondence at the video level. Additionally, the limitations of LongVA [38] may also impact the quality of clip-level captions, further contributing to this effect.

To further validate the effectiveness of the image sequence data, we tested our image sequence data on Video-LLaMA [6], a general video LLM without prior temporal training. As shown in Table 4, while the base model struggles with temporal events (F1 score of 0.2), adding image sequence (w/ IS) improves this to 3.3, showcasing initial temporal awareness. Notably, this improvement occurs even without our unified relative position tokens, using only free-form language for index representation. This confirms that sequential knowledge can be effectively transferred across different data modalities.

In addition to dense video captioning performance with common metrics, we also evaluate the impact of different

Models	**YouCook2 (DVC)**				**Charades-STA (TVG)**	
	SODA_c ↑	**CIDEr** ↑	**Meteor** ↑	**F1** ↑	**R@1 (IoU=0.5)** ↑	**R@1 (IoU=0.7)** ↑
VTimeLLM[12] (CVPR 2024)	\	\	\	\	27.5	11.4
Monmentor [29] (arXiv 2024)	\	\	\	\	26.6	11.6
TimeChat [30]* (CVPR 2024)	1.0	2.9	1.1	12.7	27.2	11.7
TimeChat + Seq2Time (**Ours**) w/o RPT	1.2	3.7	1.4	15.7	29.3	12.8
TimeChat + Seq2Time (**Ours**)	$1.3_{+30.0\%}$	$4.2_{+44.8\%}$	$1.3_{+18.2\%}$	$16.2_{+27.6\%}$	$31.2_{+14.7\%}$	$13.7_{+17.1\%}$

Table 2. Comparison on YouCook2 and Charades-STA datasets. * denotes our reproduction of TimeChat with partial training data availability, resulting in lower scores than reported [30]. RPT denotes our proposed unified relative position token for time representation.

IS	**MC**	**CS**	**YouCook2**				**Charades-STA**	
			S ↑	**C** ↑	**M** ↑	**F1** ↑	**R@0.5** ↑	**R@0.7** ↑
✓	✓	✓	1.3	4.2	1.3	16.2	31.2	13.7
✓	✓	✗	1.2	4.0	1.2	15.9	30.9	13.1
✓	✗	✗	1.4	4.3	1.4	13.3	28.8	12.5
✗	✗	✗	1.0	2.9	1.1	12.7	27.2	11.7

Table 3. Dataset ablation of Seq2Time on TimeChat. IS: image sequence data, MC: more video captions, CS: clip sequence data. Dark green and light green indicate the best and second-best results, respectively, and this color scheme applies to all tables unless stated otherwise.

Video LLaMA	**S** ↑	**C** ↑	**M** ↑	**F1** ↑
w/o IS	0.1	0.0	0.0	0.2
w/ IS	0.1	0.1	0.2	**3.3**

Table 4. Impact of image sequence data on Video-LLaMA. Training with only image sequence data enables temporal awareness as demonstrated by improved F1 scores (0.2 → 3.3).

Method	**TimeChat**	**+IS**	**+IS+MC**	**+Seq2Time**
L_{avg}	6.81	8.19	8.74	11.53
TTR	0.268	0.411	0.384	0.396

Table 5. Impact of caption quality metrics across different training data configurations. L_{avg}: average caption length, TTR: Type-Token Ratio (lexical diversity). Higher values indicate more detailed and diverse descriptions.

training datasets on the text richness of the generated captions in two aspects: generated caption length and lexical diversity. As shown in Table 5, adding new training data has a noticeable effect on the text richness of the captions. To assess text richness, we measure the average caption length (L_{avg}) and the Type-Token Ratio (TTR) [27], which quantifies lexical diversity. As indicated in the results, incorporating additional training data consistently enhances the richness and diversity of the generated captions, resulting in more descriptive and meaningful outputs.

IIC	**IIG**	**ALR**	**YouCook2**				**Charades-STA**	
			S ↑	**C** ↑	**M**↑	**F1** ↑	**R@0.5** ↑	**R@0.7)** ↑
✓	✓	✓	1.4	4.3	1.4	13.3	28.8	12.5
✗	✓	✓	1.2	3.4	1.2	12.9	27.9	11.8
✓	✗	✓	1.1	2.6	0.9	11.9	26.2	11.3
✓	✓	✗	1.0	2.7	1.0	14.4	27.2	11.4
✗	✗	✗	1.0	2.9	1.1	12.7	27.2	11.7

Table 6. Effect of individual pretext tasks in image sequence training. The first row shows results with only image sequence data. IIC: Indexed Image Captioning, IIG: Image Index Grounding, ALR: Adjacent Location Reasoning.

4.4. Image-based Pretext Tasks Ablation

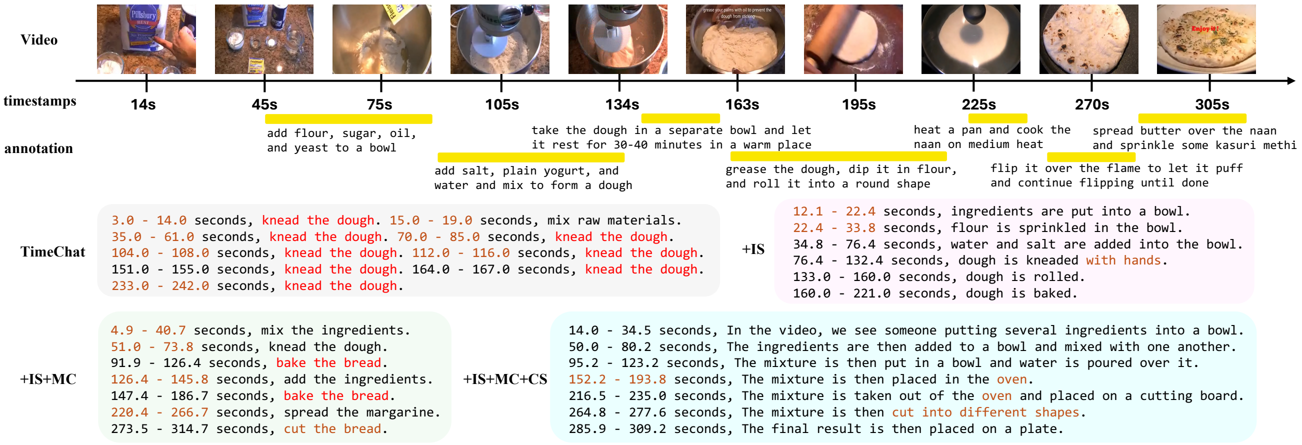
We analyze the contribution of each pretext task while controlling for training data volume by maintaining a fixed total amount of image sequence data. Table 6 shows our systematic evaluation where omitted tasks are compensated by increasing the sampling of remaining tasks (*e.g.* when ALR is removed, IIC and IIG samples increase to 150K each).

Our analysis reveals distinct roles for each task. Indexed Image Captioning (IIC) primarily **enhances text generation quality**, as evidenced by the significant CIDEr score drop when IIC is absent. Image Index Grounding (IIG) **proves crucial for overall temporal understanding**, with its removal causing performance degradation across both benchmarks, suggesting a stronger impact than IIC. Adjacent Location Reasoning (ALR) **substantially influences text generation capabilities**—its removal leads to a 37.2% decrease in CIDEr and 40% in SODA_c scores.

Importantly, comparing the baseline TimeChat with variants using only IIC and IIG shows that performance improvements depend more on task diversity than data volume—adding 300K samples of just IIC and IIG data yields only a 13.4% improvement. This underscores the importance of our complementary task design in developing robust temporal understanding capabilities.

4.5. Dataset Scaling

To investigate the scaling properties of Seq2Time, we conduct experiments with varying proportions (5% and 20%) of


Video
timestamps
14s
45s
75s
105s
134s
163s
195s
225s
270s
305s
annotation
add flour, sugar, oil, and yeast to a bowl
take the dough in a separate bowl and let it rest for 30-40 minutes in a warm place
heat a pan and cook the naan on medium heat
spread butter over the naan and sprinkle some kasuri methi
add salt, plain yogurt, and water and mix to form a dough
grease the dough, dip it in flour, and roll it into a round shape
flip it over the flame to let it puff and continue flipping until done
TimeChat
+IS
+IS+MC
+IS+MC+CS

TimeChat

```
3.0 - 14.0 seconds, knead the dough. 15.0 - 19.0 seconds, mix raw materials.
35.0 - 61.0 seconds, knead the dough. 70.0 - 85.0 seconds, knead the dough.
104.0 - 108.0 seconds, knead the dough. 112.0 - 116.0 seconds, knead the dough.
151.0 - 155.0 seconds, knead the dough. 164.0 - 167.0 seconds, knead the dough.
233.0 - 242.0 seconds, knead the dough.
```

+IS

```
12.1 - 22.4 seconds, ingredients are put into a bowl.
22.4 - 33.8 seconds, flour is sprinkled in the bowl.
34.8 - 76.4 seconds, water and salt are added into the bowl.
76.4 - 132.4 seconds, dough is kneaded with hands.
133.0 - 160.0 seconds, dough is rolled.
160.0 - 221.0 seconds, dough is baked.
```

+IS+MC

```
4.9 - 40.7 seconds, mix the ingredients.
51.0 - 73.8 seconds, knead the dough.
91.9 - 126.4 seconds, bake the bread.
126.4 - 145.8 seconds, add the ingredients.
147.4 - 186.7 seconds, bake the bread.
220.4 - 266.7 seconds, spread the margarine.
273.5 - 314.7 seconds, cut the bread.
```

+IS+MC+CS

```
14.0 - 34.5 seconds, In the video, we see someone putting several ingredients into a bowl.
50.0 - 80.2 seconds, The ingredients are then added to a bowl and mixed with one another.
95.2 - 123.2 seconds, The mixture is then put in a bowl and water is poured over it.
152.2 - 193.8 seconds, The mixture is then placed in the oven.
216.5 - 235.0 seconds, The mixture is taken out of the oven and placed on a cutting board.
264.8 - 277.6 seconds, The mixture is then cut into different shapes.
285.9 - 309.2 seconds, The final result is then placed on a plate.
```

Figure 4. Qualitative examples of our Seq2Time on TimeChat. IS: image sequence data, CS: clip sequence data, MC: more video captions. Text highlighted in **red** shows repetitive patterns in outputs, while **brown** indicates incorrect predictions in timestamps or event descriptions.

our image sequence and clip sequence data using TimeChat as the baseline model. As shown in Table 7, even with just 5% of our data, we observe notable improvements in dense video captioning performance, particularly in the CIDEr metric which measures text generation quality. The performance scales positively with data volume, showing consistent improvements across both dense video captioning and temporal video grounding tasks as we increase the proportion of Seq2Time data.

IS/CS	YouCook2				Charades-STA	
	S	C	M	F1	R@0.5	R@0.7
100%	1.3	4.2	1.3	16.2	31.2	13.7
20%	1.1	3.8	1.3	14.8	28.3	11.9
5%	1.2	3.6	1.2	15.0	26.8	11.2
0%	1.0	2.9	1.1	12.7	27.2	11.7

Table 7. Impact of Seq2Time data scaling on TimeChat. Even with 5% data, significant improvements are observed. Performance continues to scale positively with increased data volume.

4.6. Qualitative Study

To qualitatively demonstrate the effectiveness of Seq2Time, we analyze different model variants in Figure 4. The baseline **TimeChat tends to generate repetitive patterns**, *e.g.*, repeatedly mentioning *knead the dough* throughout the video when this action only occurs between 120s and 200s. This phenomenon is consistent with TimeChat's low TTR in Table 5. This limitation likely stems from insufficient captioning data in TimeIT. However, our Seq2Time, leveraging rich captions from both image and clip sequence datasets, significantly improves temporal and descriptive accuracy.

Specifically, the addition of image sequence data (IS) yields two key improvements. **First, it eliminates repetitive captioning patterns,** as indicated by the absence of repetitive patterns in the green patch. **Second, it enhances event recognition**—for example, the model accurately localizes the event *water and salt are added into the bowl* to 34.8-76.4 seconds, closely matching the ground truth of 48-79 seconds. This improvement aligns with our quantitative findings in Table 3, where image sequence data substantially improves the CIDEr score. In the full version (blue patch), the model demonstrates even **more precise temporal and descriptive capabilities**. For instance, it correctly identifies and localizes the event *the mixture is then put in a bowl and water is poured over it* to 95.2-123.2 seconds, matching the ground truth event *add salt, plain yogurt, and water and mix to form a dough* (80-133 seconds). While some fine-grained object recognition challenges still remain, temporal localization is accurate. More visualizations can be found in **Appendix B**.

Failure Case Analysis Despite overall improvements, we still observe several types of prediction errors. As illustrated in Figure 4, with only image sequence data, object recognition errors occur—for example, misidentifying a blender as hands during dough mixing. Adding more video caption data (+IS+MC) reduces but doesn't eliminate all repetitive patterns, and sometimes confuses similar objects (*e.g.*, identifying dough as bread). Even in the full version, we notice object recognition errors (pan mistaken for oven) and hallucinated events (*e.g.*, *cut into different shapes*). These issues primarily stem from visual recognition limitations and suggest that incorporating more advanced visual encoders could further improve model performance.

5. Conclusion

We propose Seq2Time to address the data scarcity challenge in training time-sensitive video LLMs. Our approach constructs training data from both image sequences and video clips in a self-supervised manner. Furthermore, we propose a unified relative position token, which bridges different sequence types by standardizing position representation in the LLM embedding space. Extensive experiments demonstrate the effectiveness and promising scalability of our approach, showing that sequential knowledge can be successfully transferred from sequence data to long video understanding. We believe our work opens several directions for future research. The framework could be extended to other sequence types, such as image patches, where patch-level correlations could provide additional supervisory signals for temporal understanding. This suggests a broader potential for leveraging various forms of sequential data to enhance the temporal capabilities of video LLMs.

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Appendix

A. Data Preparation

A.1. Image Sequence

Data Source. To construct an image sequence dataset that provides high-quality visual-text alignment, we select LLaVA-ReCap [16] as the primary source. Built on the robust vision-language model LLaVA-NeXT-34B [17], LLaVA-ReCap contains over 3.7 million image-text pairs. Its captions are detailed, providing a rich description of the visual content, as exemplified in Figure 5. These captions enable strong correspondence between visual elements and language, serving as a reliable basis for generating high-quality sequential supervision in our training. This alignment is critical for training models to understand and reason over temporally structured visual data.

Instruction Template Design. To maximize the diversity and effectiveness of the training data, we design multiple instruction templates for each pretext task using GPT-4o [28]. These templates include variations in both questions and answers to ensure robustness in model learning. Figures 6, 7, 8, 9, and 10 illustrate examples of these templates for different tasks, such as Image Index Grounding (IIG), Indexed Image Captioning (IIC), and Adjacent Location Reasoning (ALR). This variety enhances the model's ability to generalize across different types of instructions and strengthens its visual-language understanding capabilities.

A.2. Clip Sequence

Data Source. We utilize the Kinetics-700 dataset [4], a large-scale video understanding dataset comprising approximately 650,000 ten-second video clips annotated with 700 distinct human action classes. The dataset offers diverse and naturalistic videos capturing a wide range of everyday activities. For our Seq2Time, we focus on the training split, which contains about 550,000 clips, ensuring a broad spectrum of visual and temporal information for model training.

Clip Captioning with LongVA. To generate textual descriptions for the video clips, we employ LongVA [38], a state-of-the-art video captioning model. LongVA generates captions based on the visual content and the associated action label, as demonstrated in Figure 11. For instance, it accurately captures detailed descriptions like "A player in an orange jersey is leaping towards the hoop..." for basketball action clips. These captions provide contextual insights into the actions and environments depicted in the videos, enriching the clip sequence data with semantic annotations.

Despite its strengths, LongVA occasionally produces hallucinated descriptions, as illustrated in Figure 12. For example, a video showing an adult and a baby reading by a table might be misinterpreted as "a group of adults and babies..." Such hallucinations can potentially introduce noise into the dataset, affecting the reliability of the generated sequences. This highlights a trade-off between the scalability of automatic captioning and the quality of annotations.

B. Visualization

In this section, we present qualitative results to demonstrate the effectiveness of our Seq2Time. Compared with the baseline model TimeChat, Seq2Time significantly improves upon repetitive text patterns, temporal localization accuracy, and the precision of event descriptions.

In Figure 13, we analyze a video illustrating the instructions for making pancakes. TimeChat struggles to recognize ingredients in certain steps, providing incomplete descriptions such as "a bowl of eggs" and "a bowl of flour," and its temporal predictions are imprecise, resulting in a fragmented understanding of the cooking process. In contrast, Seq2Time generates accurate and comprehensive event descriptions with precise temporal annotations, such as predicting "The next step is to mix the ingredients together in a bowl" as occurring between 25.0 to 61.4 seconds, closely aligning with the ground truth annotation: "mix flour, sugar, baking powder, and salt together in a bowl" from 25 to 61 seconds. This comparison highlights Seq2Time's ability to capture finer-grained details, maintain alignment with the video's temporal structure, and robustly capture the sequential flow of actions, effectively reducing redundancies and hallucinations often present in TimeChat's outputs. These improvements underscore Seq2Time's effectiveness in enhancing temporal grounding and understanding for long videos.

In Figure 14, a video illustrating the steps for cooking eggs is analyzed. TimeChat exhibits several issues, including generating repetitive text such as "She pours some into the bowl and stirs it" across multiple timestamps and misrecognizing objects, as seen in the caption "She sets the bowl on the stove," where the "bowl" should be the "pan." In contrast, Seq2Time minimizes these repetitive patterns and provides a more coherent description of the cooking process. Although Seq2Time incorrectly predicts the timestamp for the event "She stirs the mixture again," it successfully captures the overall sequence of actions with detailed and contextually appropriate descriptions. This example highlights Seq2Time's enhanced capability to handle complex sequences with improved temporal and semantic accuracy compared to TimeChat.

In Figure 15, the video illustrates the steps for making tacos. TimeChat fails to recognize any of the correct cooking steps, producing entirely incorrect predictions and hallucinating that the video involves baking in an oven.

In contrast, our Seq2Time provides general but accurate descriptions of the steps, despite omitting some specific ingredient details. For example, Seq2Time predicts "The man adds more ingredients to the dish and continues to stir it together" between 148.1 and 259.2 seconds. While this aligns with the overall sequence, the ground truth includes finer-grained annotations, such as adding specific ingredients like cumin powder and beef.

Figure 16 presents a video of two girls preparing tofu soup. Our Seq2Time successfully captures key cooking steps, such as describing "They mix the ingredients in a pot and stir it" from 136.1 to 211.4 seconds. This aligns closely with the ground truth annotation, "add the tofu chunks and dissolve miso paste in the soup," which spans 142 to 184 seconds. In contrast, TimeChat only captures the initial scene of the video, which is less relevant to the cooking process, failing to identify any meaningful steps.

Figure 17 shows a video depicting a woman making cakes. TimeChat fails to generate relevant captions, producing incorrect descriptions, such as "a young man baking something." While Seq2Time accurately identifies basic events within the video, providing correct and relevant captions that align with the overall context.

Finally, Figure 18 shows a video of a woman preparing a salad in the kitchen. Both TimeChat and Seq2Time manage to produce correct captions for this video. However, neither model provides detailed step-by-step instructions. Instead, they capture only general actions, such as "woman talks" or "show the different ingredients," overlooking specific details of the cooking steps. This indicates an area where further refinement of both models could enhance their performance in capturing detailed procedural actions.

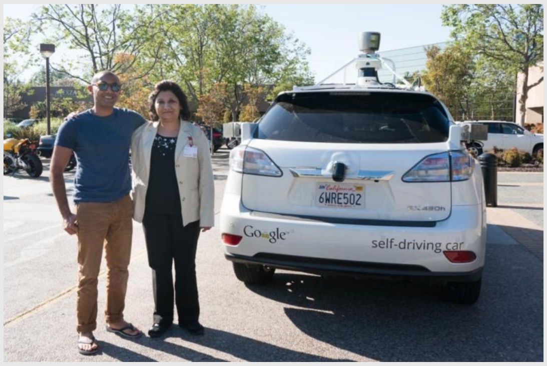
These examples collectively demonstrate the superiority of our Seq2Time in reducing hallucinations, improving temporal alignment, and providing more accurate descriptions compared to TimeChat. However, they also highlight opportunities for improvement, such as better capturing fine-grained details and enhancing object recognition in complex cooking scenarios.

C. Limitation Analysis

From Figure 13 to Figure 18, we observe the overall effectiveness of our Seq2Time in capturing key events and providing accurate temporal annotations. However, some limitations remain, which could be addressed in future work.

First, while the model generates correct captions with precise timestamps, the described events are occasionally less critical within the context of the video. For example, in Figure 16, "0.0 - 40.4 seconds, A pair of girls are preparing a meal in the kitchen," and in Figure 17, "158.7 - 166.4 seconds, The woman takes a bite of the cake and smiles at the camera," both describe valid events, but these are not essential steps in the respective cooking procedures.

Second, the model sometimes overlooks fine-grained steps that are crucial for understanding detailed processes. For instance, in Figure 15, the model predicts a general event: "33.6 - 103.1 seconds, The man prepares the ingredients for the dish and stirs them together in a pan." While this is accurate at a high level, it misses finer details such as "put olive oil," "drain off the fat," and "add chopped vegetables," which are key preparatory steps in making tacos. Addressing these limitations would enhance the granularity and relevance of the captions generated by Seq2Time.



In the image, there are two individuals standing in front of a white self-driving car. The car is equipped with a roof-mounted sensor array, which is characteristic of autonomous vehicles designed to navigate roads without human intervention. The license plate of the car reads "6WRE502". The person on the left is wearing a blue t-shirt and sunglasses, while the person on the right is dressed in a black blazer and a white shirt. Both individuals are smiling and appear to be posing for the photo. In the background, there are trees and a building, suggesting that the photo was taken in an urban or suburban setting. There is also a motorcycle parked to the left of the car. The overall scene suggests a casual, outdoor setting, possibly during a demonstration or event related to self-driving technology.

Figure 5. Illustration of an example from LLaVA-ReCap-CC3M. The caption provide details in every aspects of the image from foreground to background. For instance, even the motorcycle in the background is captured. The important descriptions are indicated in green texts.

Question Templates for Image Index Grounding with Single Target:

"Which image matches the description: {}? Please output the image index."

"Identify the image that corresponds to this caption: {}. Please provide the index."

"What is the index of the image that describes {}?"

"Can you find the image that matches this description: {}? Please give the index."

"Which image is described by {}? Please output the index."

"Find the image that matches the following description: {}. Please output the index."

"What is the index of the image that corresponds to {}?"

"Which image aligns with the caption: {}? Please provide the index."

"Identify the image matching this description: {}. Please give the index."

"What image index corresponds to the description: {}?"

Answer Templates for Image Index Grounding with Single Target:

"The image index is {}."

"You should look at image number {}."

"The correct index is {}."

"Check image of index {} for the answer."

"It corresponds to image of index {}."

"Image number {} is the correct one."

"The image matching this description is at index {}."

"You will find it at image {}."

"The right image is at index {}."

"Refer to image {}."

Figure 6. Instruction templates of image index grounding with single target image.

Question Templates for Image Index Grounding with Multiple Targets:

"Which images match the following descriptions: ",

"Identify the images corresponding to these captions: ",

"What are the indices of the images that describe the following: ",

"Can you find the images that match these descriptions: ",

"Which images are described by the following: ",

"Find the images matching these descriptions: ",

"What are the image indices that correspond to these captions: ",

"Which images align with the captions: ",

"Identify the images matching these descriptions: ",

"What image indices correspond to these descriptions: "

Following Prompt after Question:

The 1st caption is {}; the 2nd caption is {}; … <omitted>

Please output the image indices in the same order as the captions.

Answer Templates for Image Index Grounding with Multiple Targets:

"The image indices are {}.",

"You should look at image numbers {}.",

"The correct indices are {}.",

"Check images with indices {} for the answer.",

"They correspond to images of indices {}.",

"Image numbers {} are the correct ones.",

"The images matching these descriptions are at indices {}.",

"You will find them at images {}.",

"The right images are at indices {}.",

"Refer to images of indices {}."

Figure 7. Instruction templates of image index grounding with multiple target images.

Question Templates for Indexed Image Captioning with Single Target:

"Please describe the image with index {}."

"What does the image with index {} depict?"

"Can you provide the description for the image at index {}?"

"Describe the image that is indexed as {}."

"What is the caption for the image with index {}?"

"Tell me what the image at index {} shows."

"Could you describe the content of the image at index {}?"

"What does the image numbered {} describe?"

"Provide the description for the image at index {}."

"What is depicted in the image with index {}?"

Answer Templates for Indexed Image Captioning with Single Target:

"The image with index {} describes {}."

"At index {}, the image depicts {}."

"The image at index {} shows {}."

"Index {} corresponds to an image that describes {}."

"The description for the image at index {} is {}."

"For the image indexed at {}, the caption is {}."

"The image numbered {} describes {}."

"At index {}, the image is about {}."

"The caption for the image at index {} is {}."

"The image at index {} depicts {}."

Figure 8. Instruction templates of indexed image captioning with single target image.

Question Templates for Indexed Image Captioning with Multiple Targets :

"Please describe the images with the following indices: "

"What do the images at the following indices depict: "

"Can you provide descriptions for the images indexed as: "

"Describe the images corresponding to these indices: "

"What are the captions for the images with indices: "

"Tell me what the images at the following indices show: "

"Could you describe the content of the images at these indices: "

"Provide the descriptions for the images at these indices: "

"What is depicted in the images with the following indices: "

Answer Templates for Indexed Image Captioning with Multiple Targets:

"The image with index {} describes: {}."

"At index {}, the image depicts: {}."

"The image at index {} shows: {}."

"Index {} corresponds to an image that describes: {}."

"The description for the image at index {} is: {}."

"For the image indexed at {}, the caption is: {}."

"The image numbered {} describes: {}."

"At index {}, the image is about: {}."

"The caption for the image at index {} is: {}."

"The image at index {} depicts: {}."

Figure 9. Instruction templates of indexed image captioning with multiple target images.

Question Templates for Adjacent Location Reasoning:

"Which image comes right before the one depicting {}? Please output the index and describe this image."

"Which image comes right after the one depicting {}? Please output the index and describe this image."

"What is the image right before the one showing {}? Please output the index and describe the target image."

"What is the image right after the one showing {}? Please output the index and describe the target image."

"Which image is right before the one describing {}? Please output the index and describe this image."

"Which image is right after the one describing {}? Please output the index and describe this image."

"What is the image right before the one showing {}? Please provide the index and describe the image."

"What is the image right after the one showing {}? Please provide the index and describe the image."

"Identify the image that comes immediately before the one featuring {}. Please output the index and describe it."

"Identify the image that comes immediately after the one featuring {}. Please output the index and describe it."

"Which image is right before the one depicting {}? Please provide the index and describe the image."

"Which image is right after the one depicting {}? Please provide the index and describe the image."

"What is the image immediately before the one showing {}? Please output the index and describe this image."

"What is the image immediately after the one showing {}? Please output the index and describe this image."

"Which image is right before the one describing {}? Please output the index and describe the target image."

"Which image is right after the one describing {}? Please output the index and describe the target image."

"What is the image right before the one showing {}? Please provide the index and describe it."

"What is the image right after the one showing {}? Please provide the index and describe it."

"Identify the image that comes right before the one featuring {}. Please output the index and describe the image."

"Identify the image that comes right after the one featuring {}. Please output the index and describe the image."

Answer Templates for Adjacent Location Reasoning:

"Refer to image {}. It shows {}.",

"Look at image {}. It depicts {}.",

"Image {} describes {}.",

"You should check image {}. It illustrates {}.",

"The correct image is {}. It shows {}.",

"Image {} presents {}.",

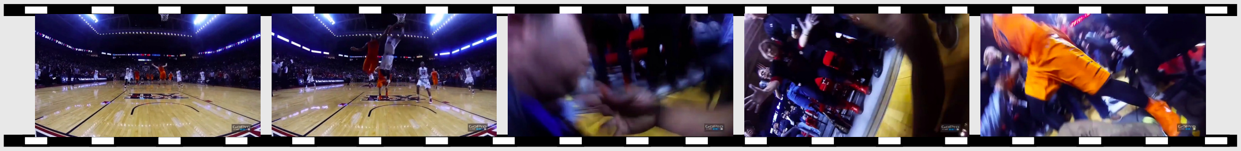
"The target image is {}. It depicts {}.",

"Refer to image {}. It describes {}.",

"You should see image {}. It illustrates {}.",

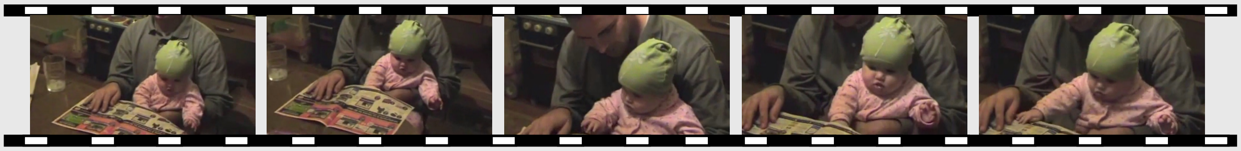
"Image {} shows {}.",

Figure 10. Instruction templates of adjacent location reasoning.



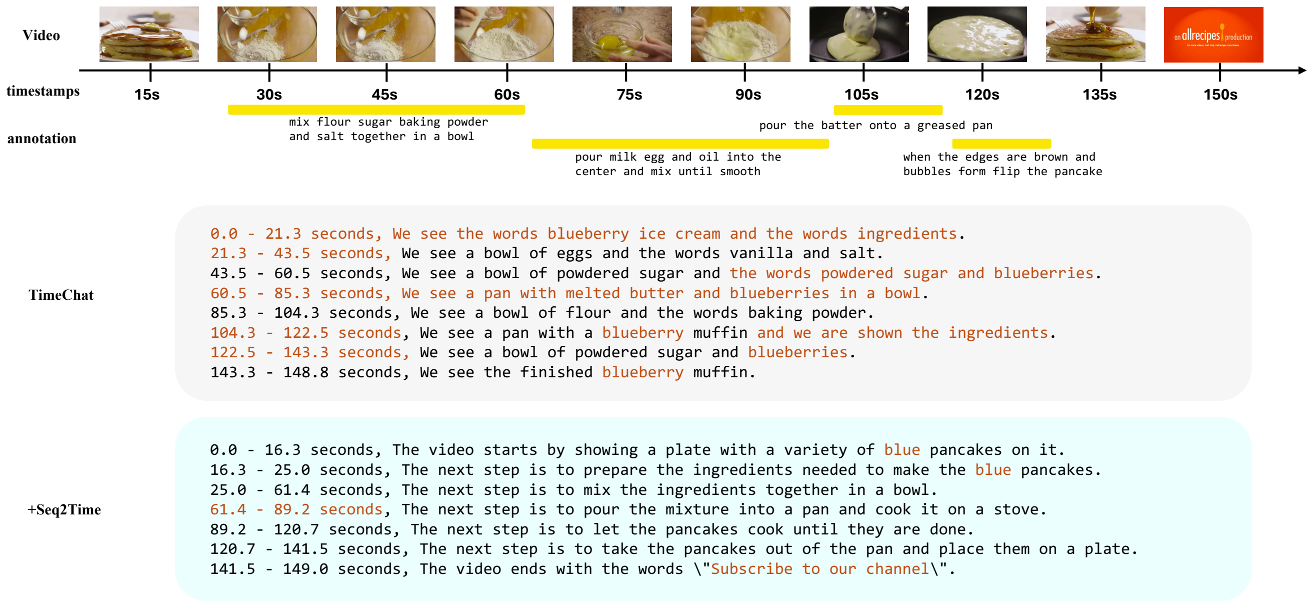
The video captures an intense moment during a basketball game. A player in an orange jersey is leaping towards the hoop, attempting to dunk or block the ball with a powerful leap, while other players from both teams are positioned strategically around the court, ready for the play's outcome. The crowd in the stands is visible, their faces a blur of anticipation and excitement as they watch the action unfold. The lighting inside the arena highlights the drama of the game, casting dramatic shadows and emphasizing the athleticism of the players on the court.

Figure 11. Instruction of an example in K700-LongVA-Captions.



In this video, ***a group of adults and babies*** *are gathered around a table, engrossed in reading a colorful newspaper. The adults and children are* ***all wearing green*** *hats with a distinctive leaf design on them, suggesting a theme or celebration related to spring or nature. The atmosphere is warm and familial, with* ***each person holding a baby*** *securely as they share the experience of reading together. The room is filled with homely warmth, and the focus is clearly on the shared joy of learning and spending time together.*

Figure 12. Instruction of a low-quality example in K700-LongVA-Captions. The incorrect descriptions are indicated by **bold red** text.


Video
timestamps
15s
30s
45s
60s
75s
90s
105s
120s
135s
150s
annotation
mix flour sugar baking powder and salt together in a bowl
pour milk egg and oil into the center and mix until smooth
pour the batter onto a greased pan
when the edges are brown and bubbles form flip the pancake
allrecipes production

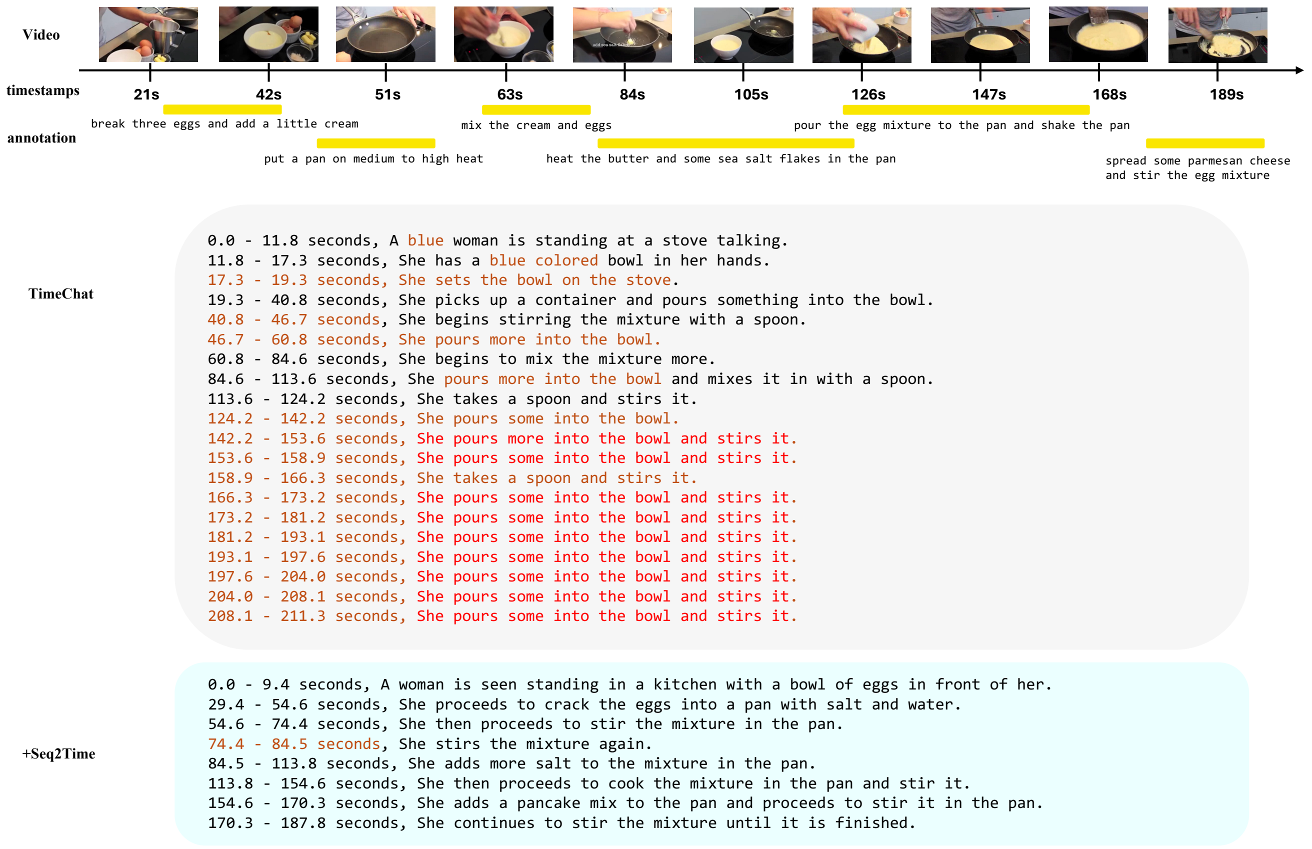
TimeChat

```
0.0 - 21.3 seconds, We see the words blueberry ice cream and the words ingredients.
21.3 - 43.5 seconds, We see a bowl of eggs and the words vanilla and salt.
43.5 - 60.5 seconds, We see a bowl of powdered sugar and the words powdered sugar and blueberries.
60.5 - 85.3 seconds, We see a pan with melted butter and blueberries in a bowl.
85.3 - 104.3 seconds, We see a bowl of flour and the words baking powder.
104.3 - 122.5 seconds, We see a pan with a blueberry muffin and we are shown the ingredients.
122.5 - 143.3 seconds, We see a bowl of powdered sugar and blueberries.
143.3 - 148.8 seconds, We see the finished blueberry muffin.
```

+Seq2Time

```
0.0 - 16.3 seconds, The video starts by showing a plate with a variety of blue pancakes on it.
16.3 - 25.0 seconds, The next step is to prepare the ingredients needed to make the blue pancakes.
25.0 - 61.4 seconds, The next step is to mix the ingredients together in a bowl.
61.4 - 89.2 seconds, The next step is to pour the mixture into a pan and cook it on a stove.
89.2 - 120.7 seconds, The next step is to let the pancakes cook until they are done.
120.7 - 141.5 seconds, The next step is to take the pancakes out of the pan and place them on a plate.
141.5 - 149.0 seconds, The video ends with the words \"Subscribe to our channel\".
```

Figure 13. Qualitative example of our Seq2Time on TimeChat. The incorrect descriptions and timestamps are indicated by brown text.


Video
timestamps
21s
42s
51s
63s
84s
105s
126s
147s
168s
189s
annotation
break three eggs and add a little cream
put a pan on medium to high heat
mix the cream and eggs
heat the butter and some sea salt flakes in the pan
pour the egg mixture to the pan and shake the pan
spread some parmesan cheese and stir the egg mixture

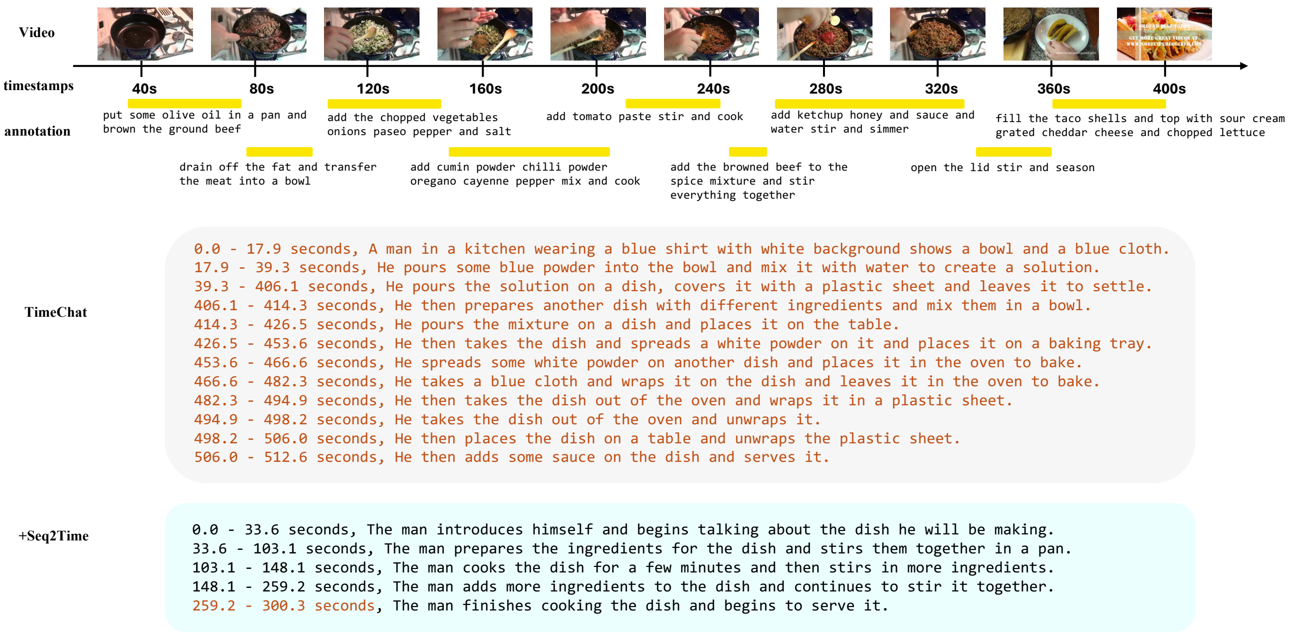
TimeChat

```
0.0 - 11.8 seconds, A blue woman is standing at a stove talking.
11.8 - 17.3 seconds, She has a blue colored bowl in her hands.
17.3 - 19.3 seconds, She sets the bowl on the stove.
19.3 - 40.8 seconds, She picks up a container and pours something into the bowl.
40.8 - 46.7 seconds, She begins stirring the mixture with a spoon.
46.7 - 60.8 seconds, She pours more into the bowl.
60.8 - 84.6 seconds, She begins to mix the mixture more.
84.6 - 113.6 seconds, She pours more into the bowl and mixes it in with a spoon.
113.6 - 124.2 seconds, She takes a spoon and stirs it.
124.2 - 142.2 seconds, She pours some into the bowl.
142.2 - 153.6 seconds, She pours more into the bowl and stirs it.
153.6 - 158.9 seconds, She pours some into the bowl and stirs it.
158.9 - 166.3 seconds, She takes a spoon and stirs it.
166.3 - 173.2 seconds, She pours some into the bowl and stirs it.
173.2 - 181.2 seconds, She pours some into the bowl and stirs it.
181.2 - 193.1 seconds, She pours some into the bowl and stirs it.
193.1 - 197.6 seconds, She pours some into the bowl and stirs it.
197.6 - 204.0 seconds, She pours some into the bowl and stirs it.
204.0 - 208.1 seconds, She pours some into the bowl and stirs it.
208.1 - 211.3 seconds, She pours some into the bowl and stirs it.
```

+Seq2Time

```
0.0 - 9.4 seconds, A woman is seen standing in a kitchen with a bowl of eggs in front of her.
29.4 - 54.6 seconds, She proceeds to crack the eggs into a pan with salt and water.
54.6 - 74.4 seconds, She then proceeds to stir the mixture in the pan.
74.4 - 84.5 seconds, She stirs the mixture again.
84.5 - 113.8 seconds, She adds more salt to the mixture in the pan.
113.8 - 154.6 seconds, She then proceeds to cook the mixture in the pan and stir it.
154.6 - 170.3 seconds, She adds a pancake mix to the pan and proceeds to stir it in the pan.
170.3 - 187.8 seconds, She continues to stir the mixture until it is finished.
```

Figure 14. Qualitative example of our Seq2Time on TimeChat. The incorrect descriptions and timestamps are indicated by brown text and repetitive text is highlighted in red.


Video
timestamps
40s
80s
120s
160s
200s
240s
280s
320s
360s
400s
annotation
put some olive oil in a pan and brown the ground beef
add the chopped vegetables onions paseo pepper and salt
add tomato paste stir and cook
add ketchup honey and sauce and water stir and simmer
fill the taco shells and top with sour cream grated cheddar cheese and chopped lettuce
drain off the fat and transfer the meat into a bowl
add cumin powder chilli powder oregano cayenne pepper mix and cook
add the browned beef to the spice mixture and stir everything together
open the lid stir and season

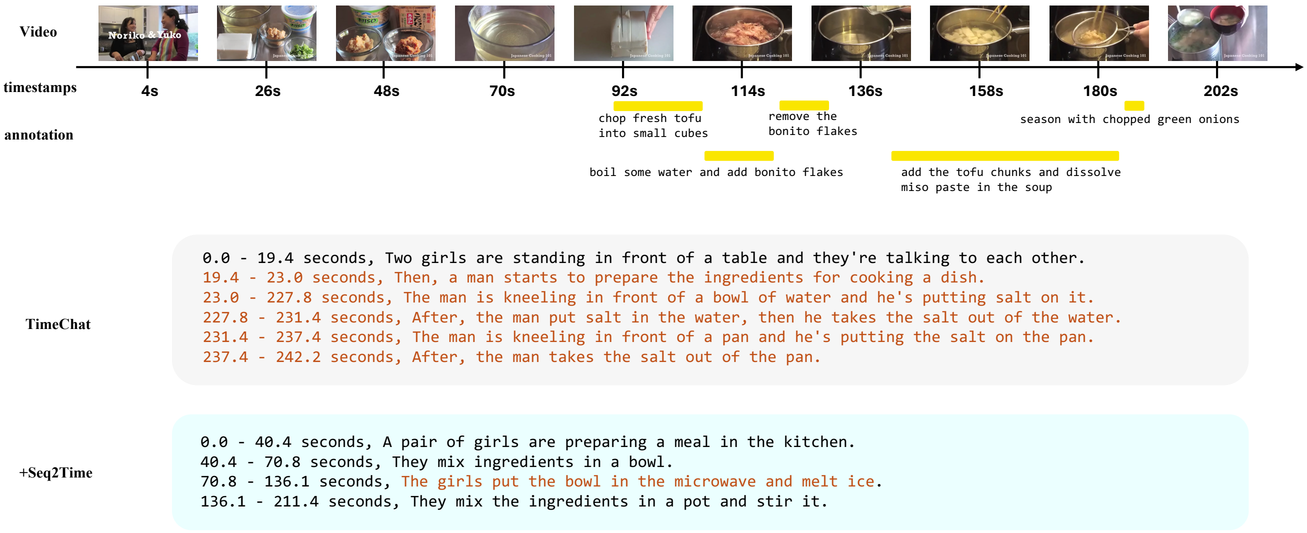
TimeChat

```
0.0 - 17.9 seconds, A man in a kitchen wearing a blue shirt with white background shows a bowl and a blue cloth.
17.9 - 39.3 seconds, He pours some blue powder into the bowl and mix it with water to create a solution.
39.3 - 406.1 seconds, He pours the solution on a dish, covers it with a plastic sheet and leaves it to settle.
406.1 - 414.3 seconds, He then prepares another dish with different ingredients and mix them in a bowl.
414.3 - 426.5 seconds, He pours the mixture on a dish and places it on the table.
426.5 - 453.6 seconds, He then takes the dish and spreads a white powder on it and places it on a baking tray.
453.6 - 466.6 seconds, He spreads some white powder on another dish and places it in the oven to bake.
466.6 - 482.3 seconds, He takes a blue cloth and wraps it on the dish and leaves it in the oven to bake.
482.3 - 494.9 seconds, He then takes the dish out of the oven and wraps it in a plastic sheet.
494.9 - 498.2 seconds, He takes the dish out of the oven and unwraps it.
498.2 - 506.0 seconds, He then places the dish on a table and unwraps the plastic sheet.
506.0 - 512.6 seconds, He then adds some sauce on the dish and serves it.
```

+Seq2Time

```
0.0 - 33.6 seconds, The man introduces himself and begins talking about the dish he will be making.
33.6 - 103.1 seconds, The man prepares the ingredients for the dish and stirs them together in a pan.
103.1 - 148.1 seconds, The man cooks the dish for a few minutes and then stirs in more ingredients.
148.1 - 259.2 seconds, The man adds more ingredients to the dish and continues to stir it together.
259.2 - 300.3 seconds, The man finishes cooking the dish and begins to serve it.
```

Figure 15. Qualitative example of our Seq2Time on TimeChat. The incorrect descriptions and timestamps are indicated by brown text.


Video
Noriko & Yuko
timestamps
4s
26s
48s
70s
92s
114s
136s
158s
180s
202s
annotation
chop fresh tofu into small cubes
remove the bonito flakes
season with chopped green onions
boil some water and add bonito flakes
add the tofu chunks and dissolve miso paste in the soup

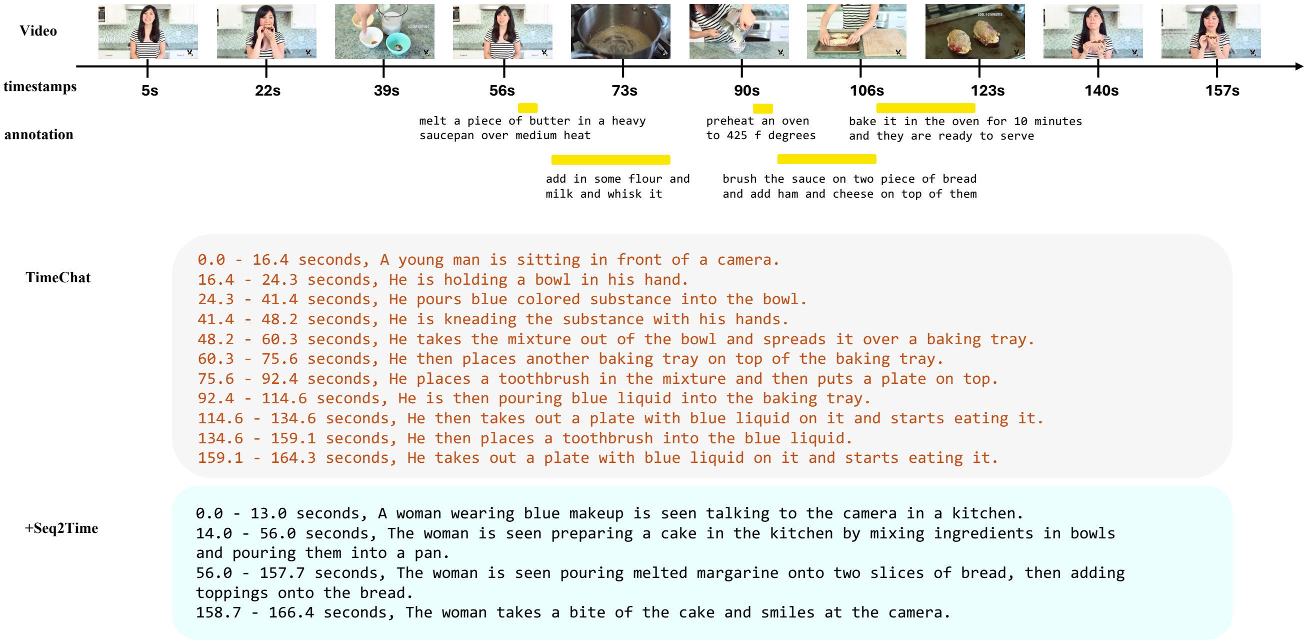
TimeChat

```
0.0 - 19.4 seconds, Two girls are standing in front of a table and they're talking to each other.
19.4 - 23.0 seconds, Then, a man starts to prepare the ingredients for cooking a dish.
23.0 - 227.8 seconds, The man is kneeling in front of a bowl of water and he's putting salt on it.
227.8 - 231.4 seconds, After, the man put salt in the water, then he takes the salt out of the water.
231.4 - 237.4 seconds, The man is kneeling in front of a pan and he's putting the salt on the pan.
237.4 - 242.2 seconds, After, the man takes the salt out of the pan.
```

+Seq2Time

```
0.0 - 40.4 seconds, A pair of girls are preparing a meal in the kitchen.
40.4 - 70.8 seconds, They mix ingredients in a bowl.
70.8 - 136.1 seconds, The girls put the bowl in the microwave and melt ice.
136.1 - 211.4 seconds, They mix the ingredients in a pot and stir it.
```

Figure 16. Qualitative example of our Seq2Time on TimeChat. The incorrect descriptions and timestamps are indicated by brown text.


Video
timestamps
5s
22s
39s
56s
73s
90s
106s
123s
140s
157s
annotation
melt a piece of butter in a heavy saucepan over medium heat
preheat an oven to 425 f degrees
bake it in the oven for 10 minutes and they are ready to serve
add in some flour and milk and whisk it
brush the sauce on two piece of bread and add ham and cheese on top of them
TimeChat
+Seq2Time

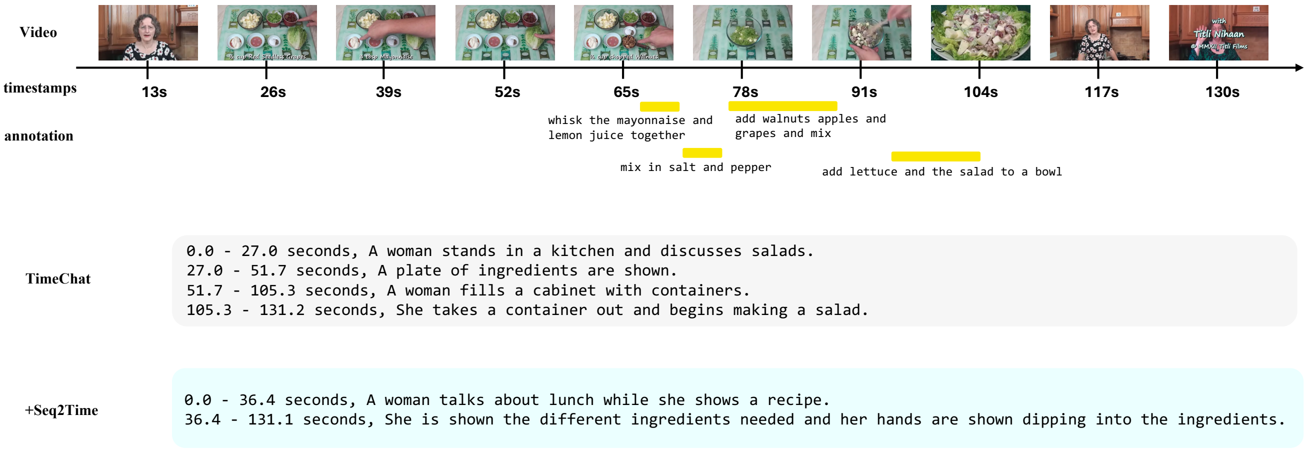
TimeChat:

```
0.0 - 16.4 seconds, A young man is sitting in front of a camera.
16.4 - 24.3 seconds, He is holding a bowl in his hand.
24.3 - 41.4 seconds, He pours blue colored substance into the bowl.
41.4 - 48.2 seconds, He is kneading the substance with his hands.
48.2 - 60.3 seconds, He takes the mixture out of the bowl and spreads it over a baking tray.
60.3 - 75.6 seconds, He then places another baking tray on top of the baking tray.
75.6 - 92.4 seconds, He places a toothbrush in the mixture and then puts a plate on top.
92.4 - 114.6 seconds, He is then pouring blue liquid into the baking tray.
114.6 - 134.6 seconds, He then takes out a plate with blue liquid on it and starts eating it.
134.6 - 159.1 seconds, He then places a toothbrush into the blue liquid.
159.1 - 164.3 seconds, He takes out a plate with blue liquid on it and starts eating it.
```

+Seq2Time:

```
0.0 - 13.0 seconds, A woman wearing blue makeup is seen talking to the camera in a kitchen.
14.0 - 56.0 seconds, The woman is seen preparing a cake in the kitchen by mixing ingredients in bowls
and pouring them into a pan.
56.0 - 157.7 seconds, The woman is seen pouring melted margarine onto two slices of bread, then adding
toppings onto the bread.
158.7 - 166.4 seconds, The woman takes a bite of the cake and smiles at the camera.
```

Figure 17. Qualitative example of our Seq2Time on TimeChat. The incorrect descriptions and timestamps are indicated by brown text.


Video
timestamps
13s
26s
39s
52s
65s
78s
91s
104s
117s
130s
annotation
whisk the mayonnaise and lemon juice together
add walnuts apples and grapes and mix
mix in salt and pepper
add lettuce and the salad to a bowl
with
Titli Nihaan
TimeChat
+Seq2Time

TimeChat:

```
0.0 - 27.0 seconds, A woman stands in a kitchen and discusses salads.
27.0 - 51.7 seconds, A plate of ingredients are shown.
51.7 - 105.3 seconds, A woman fills a cabinet with containers.
105.3 - 131.2 seconds, She takes a container out and begins making a salad.
```

+Seq2Time:

```
0.0 - 36.4 seconds, A woman talks about lunch while she shows a recipe.
36.4 - 131.1 seconds, She is shown the different ingredients needed and her hands are shown dipping into the ingredients.
```

Figure 18. Qualitative example of our Seq2Time on TimeChat. The incorrect descriptions and timestamps are indicated by brown text.