Progress-Aware Video Frame Captioning

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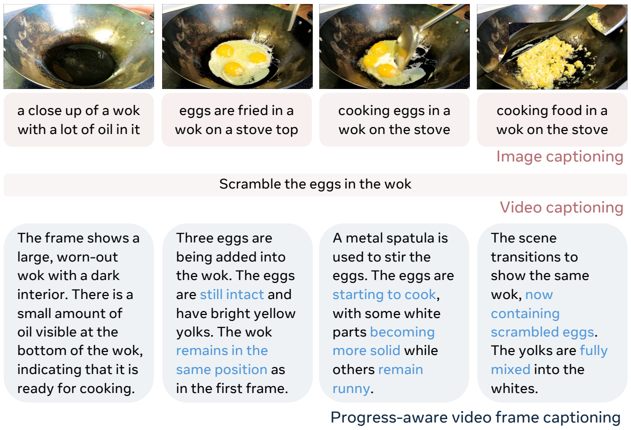
Abstract

While image captioning provides isolated descriptions for individual images, and video captioning offers one single narrative for an entire video clip, our work explores an important middle ground: progress-aware video captioning at the frame level. This novel task aims to generate temporally fine-grained captions that not only accurately describe each frame but also capture the subtle progression of actions throughout a video sequence. Despite the strong capabilities of existing leading vision language models, they often struggle to discern the nuances of frame-wise differences. To address this, we propose ProgressCaptioner, a captioning model designed to capture the fine-grained temporal dynamics within an action sequence. Alongside, we develop the FrameCap dataset to support training and the FrameCapEval benchmark to assess caption quality. The results demonstrate that ProgressCaptioner significantly surpasses leading captioning models, producing precise captions that accurately capture action progression and set a new standard for temporal precision in video captioning. Finally, we showcase practical applications of our approach, specifically in aiding keyframe selection and advancing video understanding, highlighting its broad utility.[1]

1. Introduction

Visual captioning [38]—the task of generating textual descriptions of visual content—is a fundamental problem in computer vision with extensive practical applications. Existing captioning paradigms are broadly divided into two categories: image captioning and video captioning, with a clear distinction between them. Image captioning [23] generates a single, isolated description for each image, with no contextual linkage among different images. In contrast, video captioning [1] assigns a single caption for the entire video clip, aggregating information across frames without addressing the specifics of individual frames.


a close up of a wok with a lot of oil in it

eggs are fried in a wok on a stove top

cooking eggs in a wok on the stove

cooking food in a wok on the stove

Scramble the eggs in the wok

The frame shows a large, worn-out wok with a dark interior. There is a small amount of oil visible at the bottom of the wok, indicating that it is ready for cooking.

Three eggs are being added into the wok. The eggs are still intact and have bright yellow yolks. The wok remains in the same position as in the first frame.

A metal spatula is used to stir the eggs. The eggs are starting to cook, with some white parts becoming more solid while others remain runny.

The scene transitions to show the same wok, now containing scrambled eggs. The yolks are fully mixed into the whites.

Figure 1. We propose progress-aware video frame captioning (bottom), which aims to generate a sequence of captions that capture the temporal dynamics within a video. Unlike traditional image and video captioning (top) that focus on broad event-level descriptions, our task delves into the detailed, progressive dynamics of an action, necessitating precise, temporally fine-grained capabilities. Blue text highlights how the progress-aware captions build successively on the earlier content to highlight what is changing.

Figure 1 illustrates this dichotomy. Employing an image captioning model like BLIP [37] to describe each frame of the video results in captions that are *local, not temporally context-aware*, and may exhibit little variation across the sequence. Conversely, video captioning provides a *global, not temporally fine-grained* overview of the event, as exemplified by the YouCook2 [85] ground truth label "scramble the eggs in the wok". In both scenarios, the nuances of how the action unfolds over time are missed. This raises the question: Can we develop temporally fine-grained captions that capture the subtle, progressive nature of action sequences? Figure 1 (bottom) illustrates what we seek.

Having such progress-aware captions could benefit a great variety of downstream tasks, bringing improved video understanding [73, 79], more precise video retrieval [66–68], and enriched video generation [50, 58]. Moreover, such a capability could open up new AR/VR and robotics applications. For instance, in AI coaching, a captioning system could meticulously analyze an expert's tennis forehand, simplifying the learning process for users. Similarly, for how-to video creation, it could elicit and describe the

[†] Work conducted as an independent researcher

[1] Project webpage: https://vision.cs.utexas.edu/projects/ProgressCaptioner.

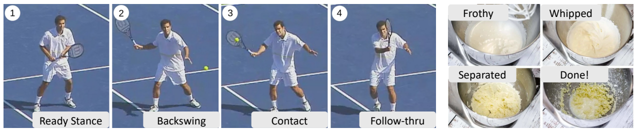


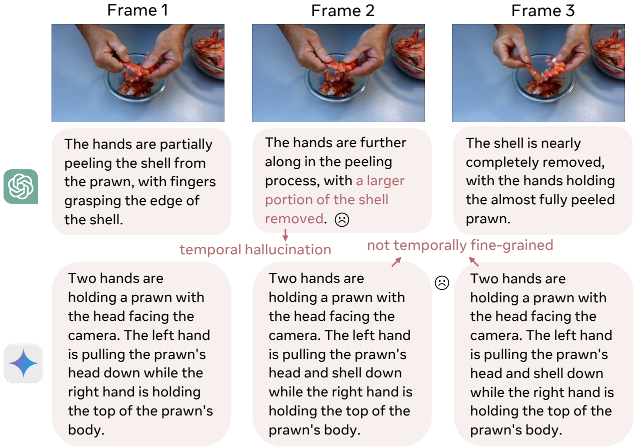
Figure 2. Use cases of video frame captioning: finer-grained captions enable detailed, step-by-step guidance for daily tasks.

key object state changes at each stage (e.g., "how to make whipped cream")—useful for both content creators as well as visually-impaired users learning a new skill. See Fig. 2.

Towards this end, we introduce a novel captioning task—*progress-aware video captioning at the frame level*. This task involves generating captions that not only coherently depict action progression but also tailor each description specifically to its corresponding frame.[2] Our task is uniquely characterized by its demand for fine-grained temporal sensitivity. By "fine-grained", we refer to generating detailed descriptions that elucidate the stages or procedural steps of the action, effectively conveying how the action is performed throughout the video sequence.

As discussed, traditional video captioning [9, 63, 70, 86] settles for broad event-level descriptions, where a description like scrambling eggs for the video in Figure 1 would be considered entirely accurate. In contrast, we seek progress-aware captions that detail each stage of the action, such as "eggs still intact", "starting to cook" and "fully mixed". While recent works [6, 8, 11, 12, 61, 83] enhance the overall descriptiveness of video captions, they continue to produce a single video-level description without distinguishing the nuances across time. Our task delves deeper, exploring how each frame contributes to the narrative of the action's progression, thereby setting a new standard for fine-grained temporal precision in video captioning.

Despite great advancements of vision language models (VLMs) [2, 33, 37, 40–42, 62, 75, 81, 83] that have markedly improved visual captioning, we observe that these models still struggle with this nuanced task. Two main issues persist: first, the lack of temporally fine-grained captions; when shown adjacent frames that depict subtle variations in action progression (such as frames 2 and 3 in Figure 3), the generated captions can be overly coarse, failing to differentiate between the frames (see row 2, Gemini-1.5-Pro's captions). Second, we identify and term a notable issue of "temporal hallucination", where the captions suggest temporal progression in disagreement with what the visual frames exhibit. See frame 2 of Figure 3, where GPT-4o's generated captions (row 1) incorrectly advance the action sequence. The prevalence of such errors can



The hands are partially peeling the shell from the prawn, with fingers grasping the edge of the shell.

The hands are further along in the peeling process, with a larger portion of the shell removed. ☹

The shell is nearly completely removed, with the hands holding the almost fully peeled prawn.

Two hands are holding a prawn with the head facing the camera. The left hand is pulling the prawn's head down while the right hand is holding the top of the prawn's body.

Two hands are holding a prawn with the head facing the camera. The left hand is pulling the prawn's head and shell down while the right hand is holding the top of the prawn's body. ☹

Two hands are holding a prawn with the head facing the camera. The left hand is pulling the prawn's head and shell down while the right hand is holding the top of the prawn's body.

Figure 3. Issues of existing VLMs in video frame captioning: (1) Lack of temporal granularity. See captions for frames 2 and 3, produced by Gemini-1.5-Pro (row 2), which fail to distinguish subtle differences between the frames. (2) Temporal hallucination. See frame 2's caption produced by GPT-4o (row 1), which inaccurately suggests progression that is not visible.

be attributed to models' reliance on the common statistics of activity sequences, which mistakenly override matching specific statements to specific frames. Meanwhile, image captioners—even if trained with fine-grained annotations—treat frames in isolation and hence lack the temporal context to say what is *progressing* versus what is *present*.

We introduce ProgressCaptioner, a model for generating progress-aware frame-level video captions. Our approach uniquely interleaves pseudo labeling with two learning stages. Stage I develops a *frame pair* captioning model, and stage II extends this to *full frame sequences*. This process also creates the FrameCap training dataset, comprising action videos along with high-quality frame-wise captions, which are initially generated by an ensemble of VLMs and then filtered using our proposed evaluation methods.

To assess the quality of frame-wise captions and benchmark ProgressCaptioner against leading VLMs, we introduce the FrameCapEval benchmark comprised of videos from four public video action datasets. ProgressCaptioner consistently outperforms leading open-source VLMs with a 1.8× to 2.7× improvement in caption quality and also achieves the highest selection rate in user studies, even surpassing the much larger proprietary models GPT-4o [2] and Gemini-1.5-Pro [53]. Finally, we highlight potential applications enabled by our advanced captions: keyframe selection and enhanced video understanding. We hope that our task, model, and benchmark can inspire future development in temporally fine-grained video captioning.

2. Related Work

Image Captioning Image captioning has been extensively studied in recent years [3, 13, 60, 76]. A related line of

[2] Without loss of generality, we obtain the input frame sequence by uniformly sampling from the action clips at a fixed rate (1FPS). These frames may or may not demonstrate visual action progression from one to the next, demanding that the model discern the difference when generating progress-aware captions.

work is image difference captioning, where the task is to describe differences between two images [27, 48, 56] or sets of images [15]. Building on the success of generative models, recent benchmarks [4, 28, 77] challenge models to distinguish between two visually similar images, advancing fine-grained image understanding. However, all the above models are restricted to static (typically synthesized) image pairs and address coarse-grained differences like object presence or absence. Temporal intricacies—accurately describing how an action progresses—remain unexplored.

Video Captioning Video captioning [1] aims to produce a single description that encapsulates a video clip. While traditional benchmarks [9, 63, 70, 86] offer a brief one-sentence caption for each video, recent efforts expand this scope, extending captioning to hours-long videos [26], enriching the granularity of details [8, 11, 61], enhancing caption uniqueness [49], integrating a causal temporal narrative [46], or introducing LLM summarization [34].

Adjacent to traditional video captioning are the tasks of visual storytelling [25, 36] (creating a coherent story for a sequence of snapshots), dense video captioning [30, 74, 87] (temporal localization and captioning of all events in an untrimmed video), audio description [20–22] (detailed narrations of visual events in videos (e.g., movies) for visually impaired audiences), and video paragraph captioning [78] (producing a multi-sentence paragraph describing the video). However, all these works still address "what is happening" at a coarse-grained event level, e.g., noting that someone is making a souffle within a specific time range. The ability to break down frame-level details—such as whisking egg whites, folding ingredients, and observing the souffle rising—is still lacking.

Vision Language Models Recent advancements in VLMs [2, 33, 37, 40–42, 62, 75, 81, 83] have greatly enhanced the capabilities of both image and video captioning. Despite their strong performance, VLMs often exhibit "hallucination" [19, 65], and preference learning [52, 84] has proven effective in mitigating this issue.

Compared to image-LMs, video-LMs crucially require the integration of temporal dynamics understanding, spurring a series of work on evaluating temporal perception [18, 39, 43, 69]. While these assessments ensure that a model can generate an accurate overall video summary or answer general questions, they entail neither temporal localization nor discernment of fine-grained differences between frames. The OSCaR benchmark [47] focuses on object state change (OSC) captioning, yet it is limited to just three frames and specifically OSC videos, with models and captions not publicly released yet preventing direct comparison. Additionally, their approach relies on human annotation and a single advanced GPT model. In contrast, our approach features a scalable data collection pipeline that reduces reliance on these labor-intensive resources, employs novel automatic evaluation tasks, and broadens the scope beyond OSC videos. Finally, unlike methods for long-form video and event localization with VLMs [10, 44, 54], our focus is distinctly more temporally fine-grained, concentrating on how individual frames evolve within a single event.

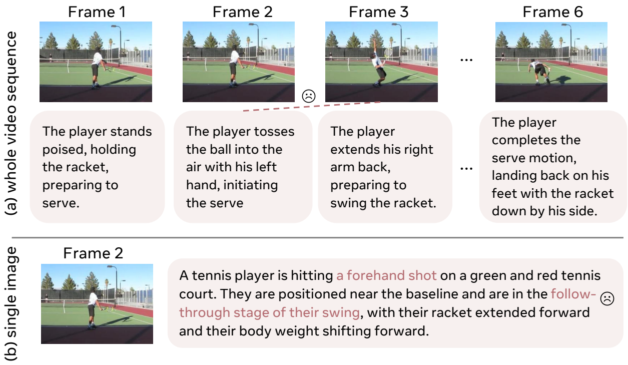

Frame 1
Frame 2
Frame 3
Frame 6
...
(a) whole video sequence
The player stands poised, holding the racket, preparing to serve.
The player tosses the ball into the air with his left hand, initiating the serve
☹
The player extends his right arm back, preparing to swing the racket.
...
The player completes the serve motion, landing back on his feet with the racket down by his side.
(b) single image
Frame 2
A tennis player is hitting a forehand shot on a green and red tennis court. They are positioned near the baseline and are in the follow-through stage of their swing, with their racket extended forward and their body weight shifting forward. ☹

Figure 4. Captioning outcomes using Gemini-1.5-Pro [53].

3. Approach

We delve into the specific challenges of our progress-aware video frame captioning problem in Sec. 3.1 and outline ProgressCaptioner's development in Sec. 3.2.

3.1. Progress-aware Video Frame Captioning

Problem Formulation Our objective is to develop a captioning model that, given a video, produces accurate temporally fine-grained captions. Formally, for a sequence of T frames, denoted as $\mathcal{V} = \{v_i\}_{i=1}^{T}$, the captioning model generates a corresponding sequence of captions $\mathcal{C} = \{c_i\}_{c=1}^{T}$, where each c_i describes the i-th frame v_i (recall we sample at 1FPS). This captioning process has three key requirements: (1) *Accuracy*, where each caption c_i must faithfully represent what is visually occurring in frame v_i, without hallucinating from the context of other frames; (2) *Temporal Specificity*, where each caption c_i specifically attends to v_i, without being overly generic to be applicable to multiple frames in the sequence; (3) *Progressive Coherence*: The sequence of captions $\{c_i\}_{i=1}^{T}$ should build upon each other to reflect the essential changes in the action over time.

FrameCap Dataset To train our captioning model, we require a dataset that pairs frame sequences ($\mathcal{V}$) with corresponding captions ($\mathcal{C}$). Existing datasets [9, 63, 70, 86] provide only a single, generic caption for an entire video clip, lacking the frame-wise caption format we need. To address this gap and train our model, we develop the FrameCap dataset. Given the prohibitive expense of collecting human-labeled caption sequences as our ground truth ($\mathcal{C}$), especially at scale, we leverage leading VLMs as powerful tools to create a pseudo caption sequence $\hat{\mathcal{C}}$ from $\mathcal{V}$. For video sources, we refer to two large-scale datasets that focus on fine-grained human activities: HowToChange [72]

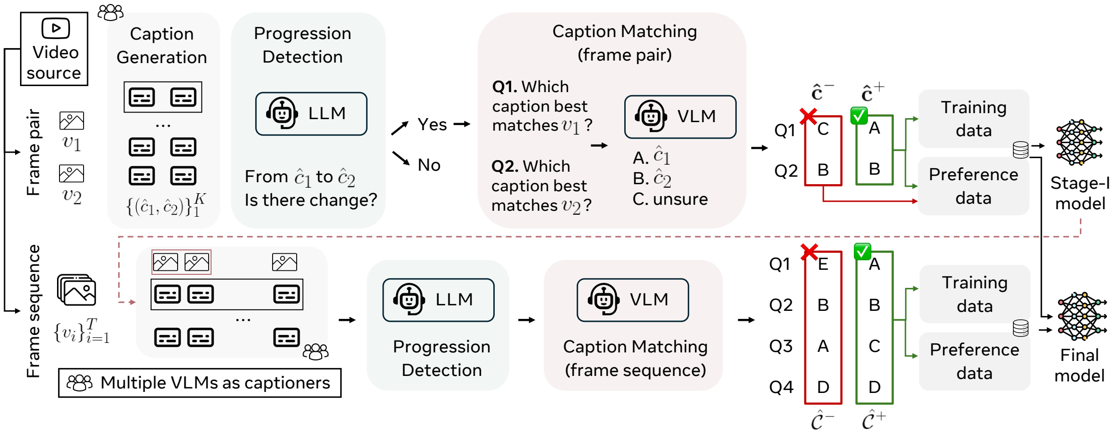


Figure 5. Framework of ProgressCaptioner, designed in two stages. In Stage-I, we prepare frame pairs and generate corresponding caption pairs using multiple VLMs. Each pair undergoes our designed progression detection and caption matching evaluations, to decide if they are selected for model supervised fine-tuning or rejected, with the latter contributing to preference data to aid in model preference learning. The Stage-I model training then proceeds using this collected data. In Stage-II, the trained stage-I model labels frame sequences with a two-frame sliding window, in conjunction with other VLMs. These sequences are again assessed through progression detection and caption matching to classify them as selected or rejected. All collected data from both stages contribute to the final training of ProgressCaptioner.

(featuring object state change videos from YouTube) and COIN [59] (featuring daily activities from YouTube).

Caption Sequence Construction Prompting VLMs for our desired caption sequence is nontrivial. We identify two key problems: (1) *Input considerations*: how many context frames from $\{v_i\}_i^T$ should be provided? (2) *Output assessment*: what issues arise in VLM-generated captions, and how can we filter to retain only high-quality ones? To explore these questions, we conduct preliminary experiments by prompting leading VLMs to perform the frame-wise captioning task. We share our findings below.

Observation I Intuitively, inputting all T frames would seem best. However, current VLM capabilities do not support this extensive context. Specifically, providing too many frames at once often leads to descriptions that lack detail and exhibit temporal inaccuracies, with VLMs also risking memory overload, as similarly observed in [11]. Conversely, providing a single frame at a time reduces the task to image captioning, which is not optimal either, resulting in captions that lack temporal context and coherence.

Figure 4 shows a representative trial with Gemini-1.5-Pro [53]. Inputting the full sequence (case (a)) yields brief per-frame descriptions with temporal misalignment (i.e., the second caption erroneously describes what is visually occurring in the third frame). On the other hand, captioning frames in isolation (case (b)) removes essential temporal context, where the model mistakes the initial stage of a tennis serve for the follow-through of a forehand swing. These findings underscore the importance of finding a balanced approach and motivate us to adopt a *frame pair* as the stepping stone of our captioning model.

Observation II Next, building upon the use of a frame pair (v_1, v_2), is the caption pair $(\hat{c}_1, \hat{c}_2)$ produced by existing VLMs of sufficient quality to be directly adopted? Our preliminary experiments reveal two main issues: (a) lack of temporal granularity, and (b) temporal hallucination, as showcased in Figure 3. To dissect these issues, we analyze the captions in relation to the visual progression between frames v_1 and v_2. Specifically, if there is a visible progression from v_1 to v_2 (e.g., the slight peeling of a shrimp's shell from frame 2 to frame 3 in Figure 3), the captions should adequately reflect this change. Overly similar captions in such a scenario signify a failure in temporal granularity. Conversely, when there is no change between frames (e.g. frames 1 and 2 in Figure 3), the captions should remain consistent. We deem it a temporal hallucination when captions erroneously indicate progression in disagreement with the visuals. This deficiency in existing VLMs motivates our development of a new captioning model and specialized evaluations for high-quality caption selection.

3.2. ProgressCaptioner

The observations above drive the design of our model, ProgressCaptioner, which unfolds in two stages. Based on our findings that current VLMs have trouble maintaining caption quality when handling extensive T-frame inputs, our approach begins with frame pair captioning. In the first stage, we develop a ProgressCaptioner to excel at describing the nuances between adjacent frames. The second stage then leverages the first-stage model to pseudo label the full T-frame sequence with a two-frame sliding window. This staged approach refines caption quality along with model development, enhancing the captioning process iteratively with more precise pseudo labels.

Frame Pair Data Preparation Starting with a frame pair

$\mathbf{v} = (v_1, v_2)$, we employ K captioning models to generate an initial set of caption pairs $\{(\hat{c}_1, \hat{c}_2)\}_1^K$. Acknowledging the potential inaccuracies in these captions, as per observation II, we design two automatic evaluation tasks to assess caption quality. The first task, *progression detection*, examines progress awareness: it checks whether the captions appropriately reflect visual changes between v_1 and v_2. Specifically, an LLM assesses each caption pair $(\hat{c}_1, \hat{c}_2)_k$ to determine if they suggest a visible physical change. We utilize majority voting across multiple LLMs' assessments for all K caption pairs to establish a consensus visual-change label. Caption pairs that align with this consensus are marked as passing; others are marked as failing.

For pairs passing progression detection, we proceed to our second evaluation task—*caption matching*—to assess how precisely $\hat{c}_1$ and $\hat{c}_2$ describe v_1 and v_2, respectively. The task is designed as a multi-choice question format, where a VLM is given $\hat{c}_1$, $\hat{c}_2$, and an "unsure" option, and tasked with matching the correct caption to each frame. A caption pair is considered good if the evaluation VLM correctly identifies $\hat{c}_1$ for v_1 and $\hat{c}_2$ for v_2. Because the captions will all be topically related, this is essentially a matching task with "hard negatives" that lets us automatically gauge the precision of the proposed captions for the target images.

This automatic pipeline distinguishes between high-quality caption pairs, denoted by $\hat{\mathbf{c}}^+ = (\hat{c}_1^+, \hat{c}_2^+)$, and those that exhibit inaccuracies or hallucinations, denoted by $\hat{\mathbf{c}}^- = (\hat{c}_1^-, \hat{c}_2^-)$, forming training data for Stage I.[3]

Stage I Training Following the success of versatile VLMs in captioning tasks [34, 42, 61, 71], we initialize ProgressCaptioner with the LLAVA-OV-7B [33] checkpoint to inherit its pretrained capabilities. Stage-I training utilizes frame and caption pair data collected on HowToChange and COIN YouTube videos $<\mathbf{v}, \hat{\mathbf{c}}^+, \hat{\mathbf{c}}^->$ through two principal methods: supervised fine-tuning (SFT) and direct preference optimization (DPO). The SFT process is straightforward given our dataset; we perform instructional tuning to tailor the general capabilities of the original VLM to our specific frame-wise captioning requirements using $<\mathbf{v}, \hat{\mathbf{c}}^+>$. The subsequent DPO step targets the prevalent issue of hallucination in VLMs and is innovatively driven by our proposed automatic evaluation critics. Preference optimization [52] in LLM training typically requires human-provided preference data to steer LLM responses towards more desirable outputs. Here, we employ progression detection and caption matching to automatically construct preference data $\hat{\mathbf{c}}^+$ and $\hat{\mathbf{c}}^-$, eliminating the reliance on manual labeling. This preference data $<\mathbf{v}, \hat{\mathbf{c}}^+, \hat{\mathbf{c}}^->$ is adopted in DPO training to further enhance model performance with feedback from LLM and VLM evaluations.

Frame Sequence Data Preparation The second stage expands our pseudo labeling scheme from 2 to T frames, where our Stage-I ProgressCaptioner first generates captions using a two-frame sliding window. To increase data diversity and volume, we also incorporate captions produced by other VLMs, with both two-frame and full T-frame contexts, since captions of low-quality are also useful (after undergoing our evaluation tasks, those that are rejected enrich the preference data). Once the initial set of caption sequences is generated, we conduct progression detection to identify M visually distinct frames from the original T-frame sequence, denoted as $\mathcal{V}_M = \{v_i\}_{i=1}^M$, using majority voting; M varies based on the distinctiveness of each frame sequence's content. The caption matching task is then employed to encompass M frames, with a selection pool of all M captions, $\hat{\mathcal{C}}_M = \{\hat{c}_i\}_{i=1}^M$, plus an "unsure" option. A high-quality caption sequence $\hat{\mathcal{C}}^+$ is identified when the evaluation VLM correctly selects $\hat{c}_i$ for v_i across all frames. Conversely, a caption sequence is deemed problematic, $\hat{\mathcal{C}}^-$, if the VLM incorrectly answers more than half of the caption selections. This process forms our Stage-II data.

Stage II Training Following the same pipeline as stage I, ProgressCaptioner is first trained through SFT using data prepared during both stages, which includes frame-caption pairs $<\mathbf{v}, \hat{\mathbf{c}}^+>$ and frame-caption sequences $<\mathcal{V}, \hat{\mathcal{C}}^+>$. Subsequently, we conduct DPO with preference data collected from both stages $<\mathbf{v}, \hat{\mathbf{c}}^+, \hat{\mathbf{c}}^->$ and $<\mathcal{V}, \hat{\mathcal{C}}^+, \hat{\mathcal{C}}^->$ to further refine performance and mitigate hallucination. This sequential approach results in our final captioning model, that accepts inputs ranging from 2 to T frames. This flexibility allows users to control the temporal context, balancing the need for local frame-wise changes (smaller window) and global event progressions (larger window). The framework is illustrated in Figure 5.

4. Experiments

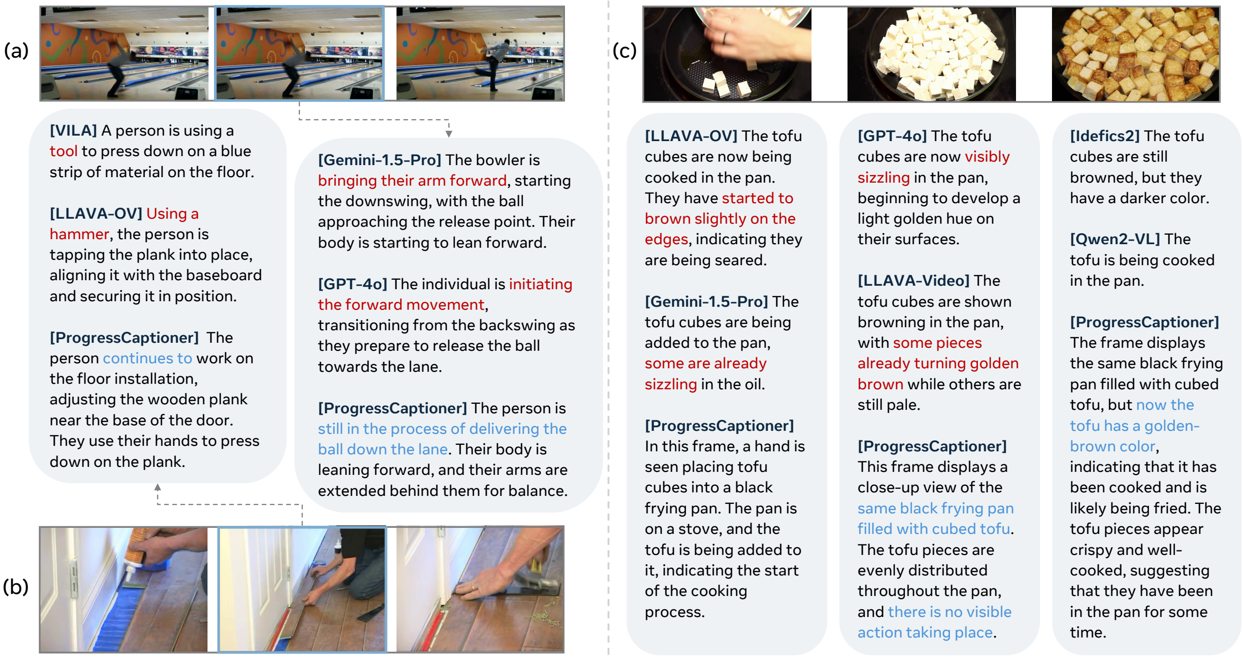
We tackle two questions below: (1) How to evaluate frame-wise caption quality of existing models? And how does ProgressCaptioner perform? (Sec. 4.1); (2) What applications are enabled by precise progress-aware captions? (Sec. 4.2)

4.1. Benchmarking Video Frame Captioning

Benchmark Data Curation We establish the FrameCapEval benchmark, featuring videos from **four action understanding datasets**: HowToChange [72] and COIN [59] (on which ProgressCaptioner was trained), along with Penn Action [82] and Kinetics [7], which are unseen in training and serve to assess generalization capabilities. We are mindful of the single frame bias [32] and manually verify all videos to exclude sequences lacking fine-grained action progression. This process yields a final set of 684 videos.

Evaluation Metrics We employ the automatic evalua-

[3] We encourage readers to view data examples provided in Supp. for a better understanding of our data refinement process, as well as details on pseudo labeling, prompts used, and the K VLMs we employ.



[VILA] A person is using a tool to press down on a blue strip of material on the floor.

[LLAVA-OV] Using a hammer, the person is tapping the plank into place, aligning it with the baseboard and securing it in position.

[ProgressCaptioner] The person continues to work on the floor installation, adjusting the wooden plank near the base of the door. They use their hands to press down on the plank.

[Gemini-1.5-Pro] The bowler is bringing their arm forward, starting the downswing, with the ball approaching the release point. Their body is starting to lean forward.

[GPT-4o] The individual is initiating the forward movement, transitioning from the backswing as they prepare to release the ball towards the lane.

[ProgressCaptioner] The person is still in the process of delivering the ball down the lane. Their body is leaning forward, and their arms are extended behind them for balance.

[LLAVA-OV] The tofu cubes are now being cooked in the pan. They have started to brown slightly on the edges, indicating they are being seared.

[Gemini-1.5-Pro] The tofu cubes are being added to the pan, some are already sizzling in the oil.

[ProgressCaptioner] In this frame, a hand is seen placing tofu cubes into a black frying pan. The pan is on a stove, and the tofu is being added to it, indicating the start of the cooking process.

[GPT-4o] The tofu cubes are now visibly sizzling in the pan, beginning to develop a light golden hue on their surfaces.

[LLAVA-Video] The tofu cubes are shown browning in the pan, with some pieces already turning golden brown while others are still pale.

[ProgressCaptioner] This frame displays a close-up view of the same black frying pan filled with cubed tofu. The tofu pieces are evenly distributed throughout the pan, and there is no visible action taking place.

[Idefics2] The tofu cubes are still browned, but they have a darker color.

[Qwen2-VL] The tofu is being cooked in the pan.

[ProgressCaptioner] The frame displays the same black frying pan filled with cubed tofu, but now the tofu has a golden-brown color, indicating that it has been cooked and is likely being fried. The tofu pieces appear crispy and well-cooked, suggesting that they have been in the pan for some time.

Figure 6. Qualitative comparisons of ProgressCaptioner with SOTA VLMs on three action sequences. For sequences (a) and (b), only the middle frame predictions are displayed. See Supp. for all models' predictions on full sequences and more examples. Inaccuracies in descriptions are highlighted in red. Even top VLMs often produce descriptions that misalign with the corresponding frames, while ProgressCaptioner delivers hallucination-free and temporally fine-grained captions, including phrases explicitly calling out progress (blue).

Model	Size	HTC		COIN		Penn&K	
		Cap	Prog	Cap	Prog	Cap	Prog
Proprietary models							
Gemini-1.5-Pro [53] (img)	-	28.4	59.7	*24.3*	58.6	15.3	51.2
Gemini-1.5-Pro [53]	-	*31.4*	63.8	**25.0**	*63.8*	17.6	*60.3*
GPT-4o [2]	-	**32.4**	*64.2*	21.3	58.4	*18.2*	**63.2**
Open-source models							
Idefics2 [31]	8B	2.0	54.4	2.9	52.2	12.5	50.9
VILA [40]	8B	6.9	53.6	5.1	48.2	15.9	51.4
Qwen2-VL [62]	7B	13.7	**69.6**	11.0	**70.8**	8.5	58.8
LLAVA-Video [83]	7B	3.9	59.3	8.8	53.0	9.7	51.8
LLAVA-OV [33] (img)	7B	5.9	56.3	17.6	55.4	11.9	55.5
LLAVA-OV [33]	7B	7.8	59.0	5.9	57.3	5.1	50.8
PL (VLM ensemble)	-	18.6	62.5	17.6	60.1	**19.3**	52.4
ProgressCaptioner (ours)	7B	**37.3**	**73.6**	**32.3**	**66.1**	**31.3**	**63.7**

Table 1. Results on the FrameCapEval Benchmark, composed of video from four public datasets. Cap and Prog denote caption matching and progression detection accuracy, respectively. PL denotes the pseudo labeling baseline adopting filtered captions from multiple VLMs. ProgressCaptioner greatly outperforms SOTA open-source VLMs and even the leading proprietary models, despite being a 7B model. The **best** results are bolded and underlined, the **second best** are bolded, and the *third best* are italicized. The results confirm our model's generalizability from in-domain datasets (HTC for HowToChange and COIN) to external datasets not seen during training (Penn&K for Penn Action and Kinetics).

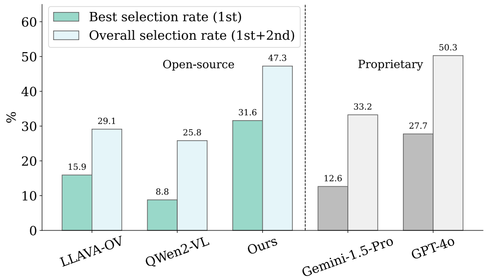


Figure 7. User study results comparing ProgressCaptioner with top competitors show it as the most preferred model (see text).

tion tasks of progression detection and caption matching (Sec. 3.2), reporting accuracy with Llama-3.1-70B-Instruct [14] as the evaluation LLM and Gemini-1.5-Pro [53] as the evaluation VLM. Additionally, we enhance our evaluation with a **user study** of 15 participants, reporting the average selection rate. See Supp. for experiments on evaluation metric reliability and full user study details.

Baselines We evaluate an array of state-of-the-art VLMs, including two proprietary models, GPT-4o [2] and Gemini-1.5-Pro [53], and five open-source models—Idefics2 [31], VILA [40], Qwen2-VL [62], LLAVA-Video [83], and LLAVA-OV [33]. We also include a pseudo labeling baseline using filtered captions produced by an ensemble of VLMs (Sec. 3), and image captioning baselines using Gemini-1.5-Pro and LLAVA-OV. We select open-source VLM variants with fewer than 10B parameters for computational efficiency and a fair comparison with our Progress-

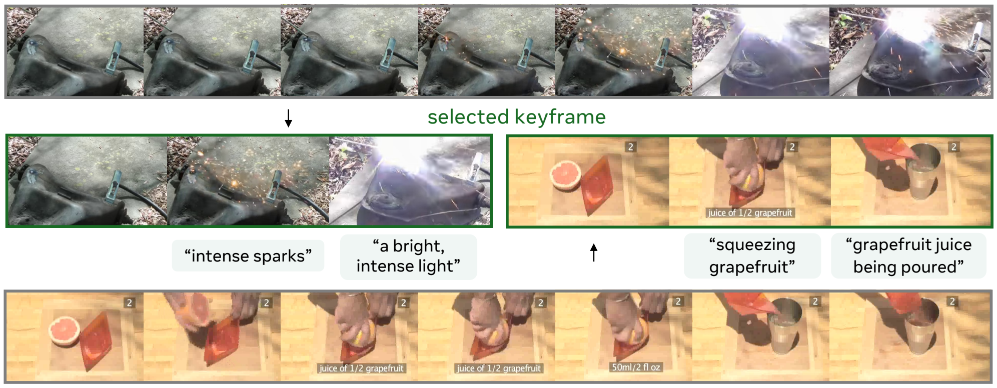


Figure 8. ProgressCaptioner facilitates keyframe selection and enriches the selected keyframes with progress-aware descriptions.

Captioner, which is an 7B model. The closed proprietary models are much larger and trained with much more extensive data; we include them as a useful reference point, but stress that they do not constitute an apples-to-apples comparison, to the disadvantage of our ProgressCaptioner.

Implementation ProgressCaptioner is constructed with SigLIP [80] as the vision encoder and Qwen2 [62] as the language model, linked through a projector, and initialized from the LLAVA-OV-7B checkpoint [33]. For benchmark evaluations in Sec. 4.1, ProgressCaptioner operates on the full T-frame sequence for a comprehensive temporal context. For applications presented in Sec. 4.2, where fine-grained analysis of local frame changes is crucial, a sliding window approach is used, with the model processing frame pairs. To ensure a fair comparison, all video baseline models are provided with the same temporal context as ProgressCaptioner across all evaluations.

Results As shown in Table 1, on the FrameCapEval benchmark, ProgressCaptioner greatly outperforms existing open-source VLMs of similar capacity and even the (much larger) latest Gemini-1.5-Pro and GPT-4o. We observe that strong language-backed VLMs like GPT-4o show high caption matching accuracy, whereas Qwen2-VL excels in progression detection, reducing hallucination. However, it tends to produce less detailed captions, leading to lower caption matching accuracy. In contrast, ProgressCaptioner effectively balances precision and detail in frame-wise captioning, consistently leading the benchmark across both in-domain and out-of-domain datasets.

Figure 6 provides qualitative comparisons on three action sequences. Consider the (a) bowling sequence for instance: baseline models erroneously suggest progression in frame 2, like "arm forward", exemplifying the common issue of temporal hallucination in current VLMs. This issue recurs in the other two sequences. Conversely, ProgressCaptioner delivers high-quality captions that precisely characterize action progress in each frame. See Supp. for more qualitative examples and an ablation of ProgressCaptioner.

User Study Figure 7 presents the user study results, where ProgressCaptioner is compared against four of the strongest competitors: LLAVA-OV, Qwen2-VL, Gemini-1.5-Pro and GPT-4o. Each participant is presented with five captions produced by these models and is tasked with selecting the top-2, with an additional "none" option if the captions are deemed inadequate. ProgressCaptioner emerges as the most preferred model, with an average best caption selection rate of 31.6%—2× to 3.6× better than the comparably sized best models from the literature [33, 62], and even surpassing top-tier proprietary models that enjoy significant scaling advantages. While our model outperforms all open-source *and* proprietary models for top-1 preference, the more forgiving top-2 metric brings the proprietary closed models back in the game, though our model remains competitive even there (50.3% for GPT-4o vs. 47.3% for ours). These findings underscore our model's strong ability to produce accurate, temporally fine-grained captions.

4.2. Applications of Video Frame Captioning

ProgressCaptioner offers progress-aware frame-wise captions, which hold great potential for many real-world applications. We explore several practical use-cases below.

Keyframe Selection Our first use-case leverages ProgressCaptioner's temporally precise captions as an intermediate representation to identify keyframes within a densely sampled sequence, aided by an LLM (see Supp. for details). Figure 8 provides two examples, showcasing how ProgressCaptioner's produced captions allow selecting distinct frames that effectively capture different stages of the welding and squeezing grapefruit action. While recent video summarization work [24] explores using VLMs and LLMs for keyframe selection, it aims to identify coarse-grained events within long videos, which is not adequate for our problem scenario. See Supp. for a side-to-side comparison and more qualitatives that underscore this distinction.

Keyframes for Action Recognition Not only is keyframe selection useful for human viewers to quickly preview a

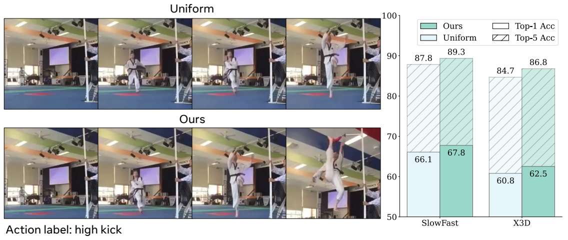


Figure 9. On Kinetics test videos, ProgressCaptioner selects four frames that are more informative of the action than uniform sampling, resulting in improved action recognition accuracy.

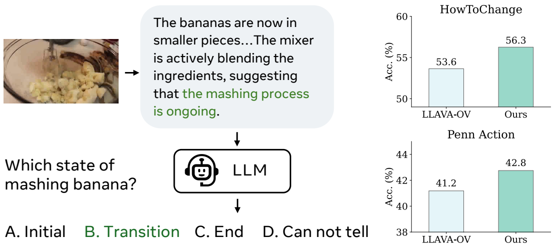

The bananas are now in smaller pieces…The mixer is actively blending the ingredients, suggesting that the mashing process is ongoing.
Which state of mashing banana?
LLM
A. Initial
B. Transition
C. End
D. Can not tell
HowToChange
Acc. (%)
60
55
50
53.6
56.3
LLAVA-OV
Ours
Penn Action
Acc. (%)
44
42
40
38
41.2
42.8
LLAVA-OV
Ours

Figure 10. ProgressCaptioner delivers precise and detailed per-frame descriptions, leading to enhanced zero-shot frame-wise classification performance when compared with LLAVA-OV.

longer video, but it can also extract the most informative portions of a video to benefit activity recognition [29]. To illustrate, we next apply our keyframe selection mechanism to Kinetics [7] Temporal [57] subset that necessitates multi-frame reasoning. Given that the original video clips are short (sampled at 1FPS, resulting in sequences of 10 frames), we employ two models that take four frames as input: Slow backbone from SlowFast [17] and X3D-XS [16]. We prompt GPT-4o to select four representative frames from frame-wise captions produced by ProgressCaptioner. We take the two model checkpoints that have been trained on the Kinetics training set and replace uniformly sampled frames with our selected keyframes during inference. Figure 9 presents a qualitative comparison, highlighting performance gains such as a +1.7% increase in top-1 accuracy for both SlowFast and X3D models. Even among just 10 candidate frames, our method's fine-grained ability to identify the 4 most informative ones translates into better recognition.

Advancing Video Understanding The precise, frame-wise captions generated by ProgressCaptioner enhance our understanding of videos. To demonstrate this, we consider two video tasks that demand temporally fine-grained understanding: (1) frame-wise classification on HowToChange [72] and Penn Action [82], and (2) video question answering (QA) on NExT-QA [69] (ATP-Hard [5]). These tasks are chosen because they challenge the model to comprehend not just the overarching content of a video, but also the more fine-grained event progression within a video. The HowToChange and Penn Action test sets provide frame-wise labels detailing object state changes or action phases, requiring frame-level understanding. Similarly, NexTQA (ATP-Hard) poses temporally challenging questions that demand multi-frame reasoning, such as determining event order, emphasizing the need for precise temporal comprehension. For baseline comparisons, we evaluate against the LLAVA-OV-7B [33] model, from which ProgressCaptioner is initialized, to highlight the enhancements that our specialized training on FrameCap brings to video understanding tasks. For the first task, as we pioneer a zero-shot, language-guided approach to this traditionally vision-centric problem (details below), no other zero-shot baselines exist. For the second task, we compare ProgressCaptioner against two existing zero-shot approaches [45, 64].

Model	Acc@C	Acc@T	Acc@All
VFC [45]	32.2	30.0	31.4
VideoAgent [64]	57.8	58.8	58.4
LLAVA-OV [33] + GPT-4o	62.6	53.4	58.8
ProgressCaptioner + GPT-4o (ours)	64.4	58.1	**61.8**

Table 2. Video QA results on NExT-QA (ATP-Hard). C and T denote causal and temporal subsets, respectively.

(a) Zero-shot Frame Classification We repurpose zero-shot frame-wise classification task into a multi-choice QA format, using frame-wise captions to guide an LLM in identifying the correct label per frame, evaluating caption accuracy and granularity (Figure 10 left). Results (Figure 10 right) show that ProgressCaptioner consistently outperforms LLAVA-OV across both datasets. Notably, our training involves no signals related to these frame-wise labels, underscoring its generalizability and effectiveness in enhancing video frame-level understanding.

(b) Video QA Finally, we report results using frame-wise descriptions for video QA, where an LLM (we use GPT-4o) is employed to answer questions on NExT-QA (ATP-Hard) set. As shown in Table 2, ProgressCaptioner achieves the best results on this benchmark, outperforming the previous leader VideoAgent [64] by +3.4%. Compared with a similar setup using LLAVA-OV, ProgressCaptioner achieves a +4.7% gain in the temporal subset, highlighting its superior ability to produce fine-grained, temporally precise descriptions and bring enhanced video understanding.

5. Conclusion

We introduce progress-aware video frame captioning, which necessitates a significant enhancement in current captioning models' capability to describe temporal action dynamics. Towards this end, we develop ProgressCaptioner and show its effectiveness in enhancing the temporal precision and alignment of captions with corresponding frames. Furthermore, we demonstrate its practical applications: keyframe selection and enhanced video understanding. By setting a new standard for temporal precision in video captioning, we hope our work inspires further development in this domain.

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