VidChain: Chain-of-Tasks with Metric-based Direct Preference Optimization for Dense Video Captioning

Ji Soo Lee*, Jongha Kim*, Jeehye Na, Jinyoung Park, Hyunwoo J. Kim†

Department of Computer Science and Engineering, Korea University
{simplewhite9, jonghakim, sonicdog00, lpmn678, hyunwoojkim}@korea.ac.kr

Abstract

Despite the advancements of Video Large Language Models (VideoLLMs) in various tasks, they struggle with fine-grained temporal understanding, such as Dense Video Captioning (DVC). DVC is a complicated task of describing all events within a video while also temporally localizing them, which integrates multiple fine-grained tasks, including video segmentation, video captioning, and temporal video grounding. Previous VideoLLMs attempt to solve DVC in a single step, failing to utilize their reasoning capability. Moreover, previous training objectives for VideoLLMs do not fully reflect the evaluation metrics, therefore not providing supervision directly aligned to target tasks. To address such a problem, we propose a novel framework named VidChain comprised of Chain-of-Tasks (CoTasks) and Metric-based Direct Preference Optimization (M-DPO). CoTasks decompose a complex task into a sequence of sub-tasks, allowing VideoLLMs to leverage their reasoning capabilities more effectively. M-DPO aligns a VideoLLM with evaluation metrics, providing fine-grained supervision to each task that is well-aligned with metrics. Applied to two different VideoLLMs, VidChain consistently improves their fine-grained video understanding, thereby outperforming previous VideoLLMs on two different DVC benchmarks and also on the temporal video grounding task.

1 Introduction

With the rapid advancement of Large Language Models (LLMs), numerous studies (Liu et al. 2023; Dai et al. 2023; Liu et al. 2024) have incorporated LLMs into video understanding tasks, leading to the emergence of Video Large Language Models (VideoLLMs). These VideoLLMs (Li et al. 2023; Zhang, Li, and Bing 2023; Maaz et al. 2024) have demonstrated strong performance in various tasks such as video question answering and video captioning, showcasing their ability to understand and utilize visual information. Despite their success, recent studies (Ren et al. 2024; Huang et al. 2024; Qian et al. 2024) have revealed that VideoLLMs exhibit unsatisfactory performance when it comes to fine-grained temporal video understanding, which often require *multiple* video-related sub-tasks given an untrimmed video.

*These authors contributed equally.

†Corresponding author.

We observe that VideoLLMs fall short of fine-grained temporal video understanding especially in Dense Video Captioning (DVC) due to two key reasons. First, the conventional practice in DVC of VideoLLMs employs one-step reasoning, which is known to be inferior to multi-step reasoning for complex tasks. In particular, existing VideoLLMs address DVC by predicting descriptions and timestamps of all events via a single-step generation. Second, the gap between training objectives (*e.g.*, next-token prediction) and evaluation metrics for DVC (*e.g.*, SODA) often leads to sub-optimal performance. The next-token prediction does not fully reflect the complex evaluation protocol which involves diverse metrics such as SODA, METEOR, and IoU.

To tackle the aforementioned issues, we introduce a novel framework, VidChain that enhances VideoLLMs' fine-grained temporal video understanding, comprised of Chain-of-Tasks (CoTasks), and Metric-based Direct Preference Optimization (M-DPO). First, we present CoTasks that decompose the objective of the challenging task into a sequence of sub-task objectives. This simple decomposition enables the model to elicit its strong reasoning capability on DVC. It eases the challenge of the complex task by solving only one sub-task at each step and enhances its capability of fine-grained temporal video understanding. Second, to further align VideoLLM with the evaluation metrics of DVC, we present M-DPO which learns the *metric preference*, a preference based on the evaluation metric such as SODA, of each sub-task that composes DVC. Following the insight from DPO (Rafailov et al. 2023), which aligns LLM with human preferences, we adopt a similar approach yet we align VideoLLMs specifically with the metric preferences.

Interestingly, we observe that this simple adaptation of evaluation metrics provides two advantages: (1) it reduces the reliance on human annotators being cost-efficient. (2) metric evaluations expand beyond the standard binary decision dataset where the labels are *continuous e.g.*, 10.0, 8.5, rather than *discrete e.g.*, win or lose. Moreover, we take account of the sequential sub-task prediction in CoTasks, where we supervise metric preferences on the *final* response of the model as well as on the *intermediate* sub-tasks that allow for more fine-grained supervision. Overall, our M-DPO is a novel method that reflects continuous characteristics of the metric-based evaluations into learning, and also provides intermediate task-specific supervision, further enhancing fine-grained video understanding of VideoLLMs. We evaluate our VidChain on two benchmarks-Activitynet Captions and YouCook2 for the challenging DVC task, and Activitynet Captions for temporal video grounding (TVG).

In sum, our contributions are three-fold:

- We propose Chain-of-Tasks (CoTasks) that decomposes a complicated task into a sequence of sub-tasks, enabling the VideoLLM to elicit its strong reasoning capability to address the challenging task of DVC.
- We present Metric-based Direct Preference Optimization (M-DPO) that aligns VideoLLM with evaluation metrics for multiple fine-grained video understanding tasks, providing supervision targeted to each task.
- Our novel framework, VidChain comprising of CoTasks and M-DPO, is generally applicable to LLM-based models which consistently improves performances when applied to baseline models.

2 Related Works

Dense Video Captioning. A fine-grained temporal understanding task for videos, Dense Video Captioning (DVC), expects the model to caption the events in the long untrimmed video, and temporally localize them. An early approaches to DVC include PDVC (Wang et al. 2021), which introduced a variant of the transformer-based DETR (Zhu et al. 2021) to predict the event captions and their timestamps. Subsequent works (Yang et al. 2023, 2024; Kim et al. 2024) explored incorporating additional data or modalities as external knowledge, such as transcribed speech or external caption to enhance performance. Another study (Zhou et al. 2024) addressed online dense video captioning, processing videos frame by frame instead of analyzing them as a whole. More recently, the emergence of Video Large Language Models has inspired efforts to evaluate these models' fine-grained video understanding capabilities with the task of DVC. However, an effective strategy to enhance VideoLLMs on DVC remains underexplored.

Video Large Language Models. Recently, multiple works (Liu et al. 2023; Dai et al. 2023; Liu et al. 2024; Chen et al. 2024; Ye et al. 2024; Ko et al. 2023a,b) incorporating Large Language Models (LLMs) for vision-language tasks have been proposed. Following those models' successes, several Video Large Language Models (VideoLLMs) have been proposed (Li et al. 2023; Zhang, Li, and Bing 2023; Maaz et al. 2024; Zhu et al. 2024; Lin et al. 2023; Li et al. 2024). Despite the remarkable performance of VideoLLMs in tasks requiring a holistic understanding of a video (*e.g.*, video-level question-answering or captioning), they often fall short in fine-grained video understanding. For instance, they often suffer in temporal grounding tasks (Krishna et al. 2017) or dense video captioning tasks (Krishna et al. 2017; Zhou, Xu, and Corso 2018), where diverse fine-grained video understanding capabilities are required. Thus, multiple works (Ren et al. 2024; Huang et al. 2024; Qian et al. 2024) have tried incorporating fine-grained information into VideoLLMs to address the problem. In this study, we propose decomposing a complicated task of DVC into simpler sub-tasks and providing supervision aligned with the desired capability, thereby enhancing VideoLLMs' capability in fine-grained understanding.

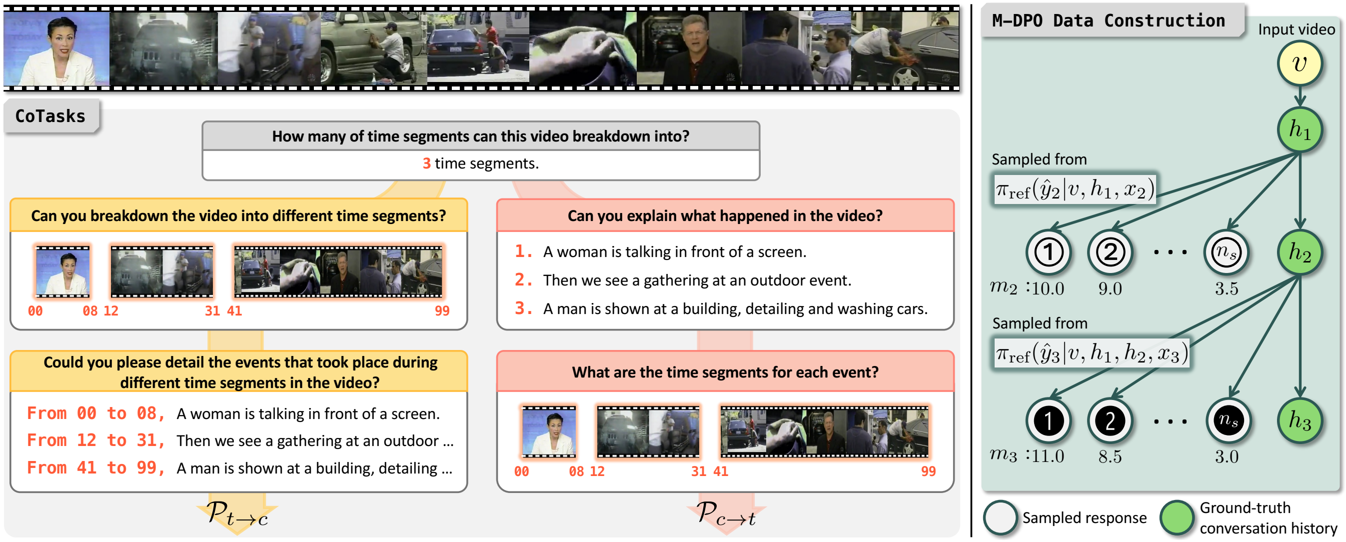
Direct Preference Optimization. To align LLM outputs with human preferences, reinforcement learning from human feedback (RLHF) (Christiano et al. 2017; Ouyang et al. 2022) has been proposed, which maximizes the likelihood gap between the preferred and unpreferred generation results. Direct preference optimization (DPO) (Rafailov et al. 2023) is derived to improve the inefficiency of RLHF, lifting the need for RL-based optimization and dedicated modules (*i.e.*, reward model), which is applied across tasks (Song et al. 2024; Xu et al. 2024; Yuan et al. 2024) to inject human preferences. Recently, some works have explored preference alignment in multimodal language models (MLLMs) to alleviate the hallucination issue (Yu et al. 2024; Ahn et al. 2024; Gunjal, Yin, and Bas 2024). However, these approaches rely on expensive models like GPT-4v (Ahn et al. 2024) or human annotators (Yu et al. 2024). In this work, we adopt the idea of Step-DPO (Lai et al. 2024) to align VideoLLM on every sub-task with the desired capability in fine-grained video understanding by defining the preferred and unpreferred responses using the metric as a criterion. Such an approach eliminates the need for extensive human labor or computation. Also, unlike conventional binary preference datasets, ours leverages continuous preferences based on the metrics.

3 Method

In this section, we first provide a brief overview of Dense Video Captioning (DVC) and Direct Preference Optimization (DPO) in Sec. 3.1. Then, we propose a Chain-of-Tasks (CoTasks) approach which eases the challenge of DVC by decomposing the task into a sequence of sub-tasks (Sec. 3.2). We then present a Metric-based DPO (M-DPO), which further aligns VideoLLMs with evaluation metrics for sub-tasks (*e.g.,* METEOR, IoU, SODA) to provide more fine-grained supervision (Sec. 3.3). Comprised of CoTasks and M-DPO, we propose a novel framework named VidChain that enhances VideoLLMs' fine-grained temporal video understanding capability.

3.1 Preliminaries

Dense Video Captioning. An challenging task of Dense Video Captioning requires the model to not only describe all events within the long untrimmed video but also temporally localize each event in time. Given a video v, the goal of DVC is to maximize the probability $p(c, t, n|v)$, where n denotes the number of events in the video, c denotes a set of event captions, and t denotes a set of event timestamps represented with start and end time boundaries for each. The key challenge is that the model must predict the three components (c, t, n) for all events given an untrimmed video v, which requires a comprehensive fine-grained understanding regarding multiple video-related tasks: video segmentation, video captioning, and temporal video grounding. The video segmentation task aims to predict the number of event sequences the video breaks down into. Video captioning focuses on describing the events in the video. The temporal



(a) (b) (c)

Figure 1: **Illustration of our CoTasks approach (left) and data construction process for M-DPO (right).** The left figure depicts the CoTasks approach of VidChain, which decomposes DVC into a sequence of sub-tasks in two different reasoning paths. After predicting the number of events, timestamp prediction and caption generation are done in path $\mathcal{P}_{t\to c}$ as shown in (a), while the order of two tasks is interchanged in path $\mathcal{P}_{c\to t}$ as in (b). The right figure (c) represents the data construction of M-DPO, where we sample n_s response of $\hat{y}_3$ (filled black circles) as well as the intermediate sub-task response $\hat{y}_2$ (hollow black circles) of CoTask for the given video v. The m_2 and m_3 denote the task-specific evaluation metric values, *e.g.*, SODA$_c$, METEOR, IoU, of each sampled response.

video grounding task aims to identify the timestamps of an event given its event description. Typically, VideoLLMs address DVC by predicting (c, t, n) in a single step, which imposes more challenge on the task.

Direct Preference Optimization. Direct Preference Optimization (DPO) (Rafailov et al. 2023) aligns Large Language Models' output with human preferences. Often, the alignment involves further finetuning a supervised finetuned model. For optimization, DPO adopts a pairwise preference dataset $\mathcal{D}_{\text{DPO}}$, where each sample comprises a pair of preferred and dispreferred responses. To construct the dataset, several responses $\hat{y}$ are first sampled from the reference model π_{ref} given a prompt x. Then, those responses are annotated according to the human preferences by comparing sampled responses in a pair-wise manner where $\hat{y}^w$ and $\hat{y}^l$ denote the preferred and dispreferred response respectively, *i.e.*, $\hat{y}^w \succ \hat{y}^l|x$. Hence, the objective of DPO, $\mathcal{L}_{\text{DPO}}$, is formally defined as follows:

$$\mathcal{L}_{\text{DPO}}(\pi_\theta;\pi_{\text{ref}}) = -\mathbb{E}_{(v,x,\hat{y}^w,\hat{y}^l)\sim\mathcal{D}_{\text{DPO}}} \left[\log\sigma\Big(\beta\cdot r(\hat{y}^w;v,x) - \beta\cdot r(\hat{y}^l;v,x)\Big)\right], \quad (1)$$

where $r(y;v,x) = \log\frac{\pi_\theta(y|v,x)}{\pi_{\text{ref}}(y|v,x)}$. This is identical to the original DPO, yet we include video v to account for the video context. $\sigma(\cdot)$ is the sigmoid function, π_θ is the model to be optimized, which is initialized to π_{ref}, and β is a hyperparameter that controls the distribution disparity of π_θ from the reference model π_{ref}. Overall, the model is trained to increase the likelihood of the preferred responses relative to that of dispreferred responses.

3.2 Chain-of-Tasks

To address the lack of fine-grained temporal understanding of VideoLLMs, especially in DVC that encompasses multiple video-related tasks, we propose a novel approach Chain-of-Tasks. Most prior works (Ren et al. 2024; Qian et al. 2024; Huang et al. 2024; Yang et al. 2023) address DVC by directly predicting (c,t,n) given v within a single step. Yet, this approach imposes more challenges on the task for the VideoLLM, as it obstructs the model from leveraging its strong reasoning capability. Hence, in CoTasks, we first decompose the objective of DVC into a series of sequential sub-task objectives. Then we prompt each task corresponding to each objective to the VideoLLM in the form of a multi-turn QA conversation. Such an approach eases the challenge of DVC by solving only one sub-task at each turn and further enhances a VideoLLM's capability in fine-grained temporal video understanding.

Objective Decomposition. Objective of DVC can be decomposed in two different reasoning paths, $\mathcal{P}_{t\to c}$ and $\mathcal{P}_{c\to t}$:

$$p(c,t,n|v) = p(c|v,n,t)p(t|v,n)p(n|v) \quad (\mathcal{P}_{t\to c}) \quad (2)$$
$$= p(t|v,n,c)p(c|v,n)p(n|v) \quad (\mathcal{P}_{c\to t}). \quad (3)$$

In the case of $\mathcal{P}_{t\to c}$ in Eq. (2), the prediction of (c,t,n) given a video v breaks down into three sequential tasks.

First, $p(n|v)$ represents the task of predicting the number of events in the video, while the following $p(t|v, n)$ represents the task of the timestamp prediction given the total number of events n, and the final $p(c|v, n, t)$ indicates caption generation for each event given the video with its t and n. The other path $\mathcal{P}_{c\to t}$ in Eq. (3) is also similarly defined, except that the order of the caption generation and the timestamp prediction tasks are interchanged. Based on this decomposition, we cast the task of DVC as a multi-turn prediction, where the model sequentially solves different tasks at each turn to tackle the challenging task. An example of our multi-turn approach, namely CoTasks, is illustrated in Fig. 1.(a) and 1.(b), each corresponding to $\mathcal{P}_{t\to c}$, and $\mathcal{P}_{c\to t}$.

Training data construction for CoTasks. $\mathcal{D}_{\text{CT}}$ is a multi-turn conversation dataset used for training VideoLLMs to reason in a CoTasks manner. We build CoTasks samples using the original DVC dataset (*e.g*., ActivityNet or YouCook2), by converting the original single-turn conversation samples into multi-turn CoTasks samples of both $\mathcal{P}_{t\to c}$ and $\mathcal{P}_{c\to t}$ types. We construct 10K and 1K samples for ActivtyNet and YouCook respectively for each path using the pre-defined templates, where the templates are provided in the supplement. Note we refer to each of the two types of dataset as $\mathcal{D}_{t\to c}$ and $\mathcal{D}_{c\to t}$, respectively. Then, we combine our obtained dataset with the DVC QA pairs and dialogues following VTimeLLM (Huang et al. 2024). Note that we adopt the full benchmark dataset unlike VTimeLLM, which only uses a selected subset for training. This results in $\mathcal{D}_{\text{CT}}$ of size of 50K for ActivityNet and 6K for YouCook2. Overall, we use $\mathcal{D}_{\text{CT}}$ to finetune VideoLLMs, enhancing their performance on fine-grained video understanding tasks, including DVC and its sub-tasks. Further details are in the supplement.

Inference pipeline of CoTasks. Since $\mathcal{D}_{\text{CT}}$ includes both samples of $\mathcal{D}_{t\to c}$ and $\mathcal{D}_{c\to t}$, the VideoLLM trained with $\mathcal{D}_{\text{CT}}$ can take either reasoning path during inference to address DVC. To encourage the model to take a certain path, we prompt the model with path-specific prompts. For instance, for $\mathcal{P}_{c\to t}$, we prompt "Can you explain what happened in the video?" to encourage the generation of event captions first, after addressing the common task for both paths, *i.e.*, the number of event predictions. In our experiments, we provide results in both inference paths.

3.3 Metric-based Direct Preference Optimization

Although CoTasks enhances VideoLLMs in fine-grained video understanding tasks, the next-token prediction objective does not fully reflect the complex evaluation protocol which involves diverse metrics such as SODA, METEOR, and IoU. Therefore, we propose a novel optimization method named Metric-based Direct Preference Optimization (M-DPO). Inspired by DPO, which aligns a model with human preferences, M-DPO aligns the VideoLLM with metric preferences, where the evaluation metric for tasks within CoTasks is adopted as criteria to determine preferred and dispreferred responses. This approach enables more fine-grained metric preference alignment of the VideoLLM as it not only supervises the *final* response but also across the *intermediate* responses within CoTasks. In the following sections, we first describe the process of constructing a dataset used for M-DPO training, which adopts metrics as criteria. Then, we introduce the overall training objective of M-DPO. Finally, we present a preference gap-aware M-DPO, which is an extension of M-DPO equipped with a tailored training scheme reflecting the continuous nature of metrics.

Training data construction for M-DPO. $\mathcal{D}_{\text{M-DPO}}$ is a preference dataset used for further aligning a VideoLLM with metric preferences, where each sample includes a pair of preferred and dispreferred responses for each specific task in the CoTask approach. To obtain a preference pair, n_s number of responses are first sampled for each intermediate k-th task given a video v, prompt x_k for k-th task, and the conversation history $h_{<k}$ that consists of prompts $x_{<k}$ and ground-truth responses $y_{<k}$ of previous $k-1$ tasks. Starting from $k = 2$, a single sampled response $\hat{y}_k$ is represented as:

$$\hat{y}_k \sim \pi_{\text{ref}}(\hat{y}_k|v, h_{<k}, x_k), \tag{4}$$

where the reference model π_{ref} is a VideoLLM trained with $\mathcal{D}_{\text{CT}}$ for CoTasks, and $h_{<2}$ is the ground-truth conversation history consisting of the prompt x_1 and ground-truth response y_1 corresponding to $p(n|v)$. For instance, in $\mathcal{P}_{t\to c}$ path of CoTasks, $\hat{y}_3$ is a response sampled from $\pi_{\text{ref}}(\hat{y}_3|v, h_{<3}, x_3)$, which models $p(c|v, n, t)$. Similarly, $\hat{y}_2$ is a response modeling $p(t|v, n)$. With the n_s sampled responses for each task, $\binom{n_s}{2}$ pairs of responses are obtained. Then, for each pair, a response $\hat{y}_k$ with a higher evaluation metric value $m_k = \mathcal{M}_k(\hat{y}_k, y_k)$ is set as the preferred response $\hat{y}_k^w$, and the other response is set as the dispreferred response $\hat{y}_k^l$, where y_k denotes ground-truth response of k-th task, and $\mathcal{M}_k$ denotes a metric corresponding to k-th task (*i.e.*, METEOR, IoU, SODA$_c$). In other words, $\hat{y}_k^w \succ \hat{y}_k^l|v, h_{<k}, x_k$, given $m_k^w > m_k^l$. The illustration of our $\mathcal{D}_{\text{M-DPO}}$ construction process is in Fig 1. (c).

Training objective of M-DPO. With $\mathcal{D}_{\text{M-DPO}}$, the VideoLLM is further trained to align with the metric preferences. Formally, the M-DPO loss regarding a single sample composed of ($\hat{y}_k^w$, $\hat{y}_k^l$, m_k^w, m_k^l, v, $h_{<k}$, x_k) is defined as:

$$\begin{aligned}&\mathcal{L}_s(\hat{y}_k^w, \hat{y}_k^l; v, h_{<k}, x_k) = \\ &\left[\log \sigma \left(\beta r(\hat{y}_k^w; v, h_{<k}, x_k) - \beta r(\hat{y}_k^l; v, h_{<k}, x_k)\right)\right],\end{aligned} \tag{5}$$

where σ denotes the sigmoid function, $r(\hat{y}_k; v, h_{<k}, x_k) = \log \frac{\pi_\theta(\hat{y}_k|v,h_{<k},x_k)}{\pi_{\text{ref}}(\hat{y}_k|v,h_{<k},x_k)}$ denotes a likelihood ratio, π_θ denotes the target model to be optimized, and β is a hyperparameter controlling the distribution disparity of π_θ from the reference model π_{ref}. Thus, by minimizing the given loss, it encourages the model to learn the metric-based preference on the k-th task by enlarging the gap of the likelihood ratio between preferred and dispreferred responses in terms of the target metric. Then, the basic version of M-DPO training objective, $\mathcal{L}_{\text{M-DPO}^-}$, excluding the preference gap-aware module described in the following section, is defined as below, with the loss averaged across all samples in $\mathcal{D}_{\text{M-DPO}}$:

$$\begin{aligned}&\mathcal{L}_{\text{M-DPO}^-}(\pi_\theta; \pi_{\text{ref}}) = \\ &\qquad - \mathbb{E}_{\mathcal{D}_{\text{M-DPO}}}\left[\mathcal{L}_s\left(\hat{y}_k^w, \hat{y}_k^l; v, h_{<k}, x_k\right)\right].\end{aligned} \tag{6}$$

	size	ActivityNet SODA$_c$	ActivityNet METEOR	ActivityNet CIDEr	YouCook2 SODA$_c$	YouCook2 METEOR	YouCook2 CIDEr
VideoChat (Li et al. 2023)	7B	0.9	0.9	2.2	-	-	-
VideoLLaMA (Zhang, Li, and Bing 2023)	7B	1.9	1.9	5.8	-	-	-
VideoChatGPT (Maaz et al. 2024)	7B	1.9	2.1	5.8	-	-	-
TimeChat (Ren et al. 2024)	13B	-	-	-	3.4	-	11.0
VTimeLLM (Huang et al. 2024)	13B	5.9	6.7	27.2	-	-	-
VTimeLLM† (Huang et al. 2024) (Baseline)	7B	5.8	6.8	27.6	3.4	3.5	10.7
VTimeLLM + VidChain-$\mathcal{P}_{t\to c}$ **(Ours)**	7B	6.9	7.1	29.1	**4.6**	**4.9**	**17.6**
VTimeLLM + VidChain-$\mathcal{P}_{c\to t}$ **(Ours)**	7B	**7.2**	**7.7**	**34.7**	4.3	4.5	16.3
VideoLLaMA2† (Cheng et al. 2024) (Baseline)	7B	7.2	7.7	32.9	3.3	3.5	12.3
VideoLLaMA2 + VidChain-$\mathcal{P}_{t\to c}$ **(Ours)**	7B	8.2	8.7	43.1	4.6	5.5	22.3
VideoLLaMA2 + VidChain-$\mathcal{P}_{c\to t}$ **(Ours)**	7B	**8.8**	**8.8**	**43.9**	**4.8**	**5.6**	**23.8**

Table 1: **Comparison of VideoLLMs on DVC.** Baseline+VidChain-$\mathcal{P}_{t\to c}$ and Baseline+VidChain-$\mathcal{P}_{c\to t}$ are identical models trained with $\mathcal{D}_{\text{CT}}$ which adopt two different reasoning path prompts for inference, $\mathcal{P}_{t\to c}$ and $\mathcal{P}_{c\to t}$ respectively, and size denotes LM size. See Sec. 3.2 for more detail. † denotes reproduced results adopting the full benchmark dataset.

	size	R@0.3	R@0.5	R@0.7	mIoU
VideoChat	7B	8.8	3.7	1.5	7.2
VideoLLaMA	7B	6.9	2.1	0.8	6.5
VideoChatGPT	7B	26.4	13.6	6.1	18.9
VTimeLLM	13B	44.8	29.5	14.2	31.4
VTimeLLM (Baseline)	7B	44.0	27.8	14.3	30.4
VTimeLLM* (TVG only)	7B	55.8	35.0	18.9	37.9
VTimeLLM + VidChain **(Ours)**	7B	**61.4**	**43.8**	**25.7**	**43.5**
VideoLLaMA2 (Baseline)	7B	49.4	26.8	15.0	33.9
VideoLLaMA2* (TVG only)	7B	59.9	41.5	22.5	42.2
VideoLLaMA2 + VidChain **(Ours)**	7B	**63.3**	**44.8**	**25.2**	**44.1**

Table 2: **Comparison of VideoLLMs on TVG.** We adopt the task-specific prompt for TVG instead of two different inference prompts (*i.e.*, $P_{t\to c}$, and $P_{c\to t}$) specifically defined for DVC, since they are not applicable to TVG. * indicates the model further trained on the corresponding TVG dataset.

	ActivityNet SODA$_c$	ActivityNet METEOR	YouCook2 SODA$_c$	YouCook2 METEOR
VTimeLLM				
Baseline	5.8	6.8	3.4	3.5
+ CoTasks-$\mathcal{P}_{t\to c}$	6.7	7.6	4.1	4.4
+ VidChain-$\mathcal{P}_{t\to c}$	**7.2**	**7.7**	**4.6**	**4.9**
+ CoTasks-$\mathcal{P}_{c\to t}$	6.5	**7.4**	3.8	4.3
+ VidChain-$\mathcal{P}_{c\to t}$	**6.9**	7.1	**4.3**	**4.5**
VideoLLaMA2				
Baseline	7.2	7.7	3.3	3.5
+ CoTasks-$\mathcal{P}_{t\to c}$	7.5	8.3	4.2	5.1
+ VidChain-$\mathcal{P}_{t\to c}$	**8.2**	**8.7**	**4.6**	**5.5**
+ CoTasks-$\mathcal{P}_{c\to t}$	7.7	8.5	4.5	5.5
+ VidChain-$\mathcal{P}_{c\to t}$	**8.8**	**8.8**	**4.8**	**5.6**

Table 3: **Ablation study on components of VidChain.** VidChain denotes CoTasks + M-DPO.

Note π_θ is built by adding LoRA modules after the initialization with π_{ref}, and LoRA modules in π_θ are only trainable parameters, and π_{ref} is left unchanged.

Preference gap-aware M-DPO. Training data for conventional DPO only includes *binary* preferences $\hat{y}^w$ and $\hat{y}^l$, which only indicates whether a response is preferred or not. On the contrary, data in $\mathcal{D}_{\text{M-DPO}}$ also comprises *continuous* preferences m_k^w and m_k^l which not only indicates whether a response is preferred or not but also reveals *how much* as it is built on continuous metrics. We observe that when optimizing with such continuous preferences, taking the gap of preferences between $\hat{y}_k^w$ and $\hat{y}_k^l$ into account further facilitates the proper training. To this end, we propose $\mathcal{L}_{\text{M-DPO}}$, an advanced version of $\mathcal{L}_{\text{M-DPO}^-}$ by modifying Eq. (6) as:

$$\mathcal{L}_{\text{M-DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{\mathcal{D}_{\text{M-DPO}}} \left[\mathbb{1}\left(m_k^w - m_k^l > \gamma\right) \cdot \mathcal{L}_s\left(\hat{y}_k^w, \hat{y}_k^l; v, h_{<k}, x_k\right)\right], \tag{7}$$

where $\mathbb{1}(\cdot)$ denotes an indicator function. Concretely, we only calculate losses on preference pairs where the gap of the evaluation metrics between the preferred and dispreferred response is above a certain threshold γ, which is a hyperparameter. Such an approach alleviates difficulties in optimizing pairs with subtle differences in metrics, thereby facilitating the overall optimization process. In the following sections, the term 'M-DPO' refers to $\mathcal{L}_{\text{M-DPO}}$ in Eq. (7) instead of $\mathcal{L}_{\text{M-DPO}^-}$ in Eq. (6) unless specified. Overall, we propose a novel framework named VidChain comprised of CoTasks and M-DPO which effectively enhances the fine-grained temporal video understanding of VideoLLMs.

4 Experiments

4.1 Benchmarks

Dense Video Captioning. We experiment on two different dense video captioning benchmarks, ActivityNet Captions (Krishna et al. 2017) and YouCook2 (Zhou, Xu, and Corso 2018). As evaluation metrics, we adopt SODA$_c$ (Fujita et al. 2020), METEOR (Banerjee and Lavie 2005), and CIDEr (Vedantam, Lawrence Zitnick, and Parikh 2015) following previous works (Huang et al. 2024; Qian et al. 2024).

Temporal Video Grounding. For temporal video grounding, we use ActivityNet Captions dataset (Krishna et al.

Dataset	var.	Method	Acc(↑)	KL-Div(↓)
ActivityNet	1.17	Baseline	40%	0.09
		+ VidChain	**70%**	**0.04**
YouCook2	7.79	Baseline	8%	0.38
		+ VidChain	**16%**	**0.06**

Table 4: **Performance on $p(n|v)$ of CoTasks**. We evaluate segmentation accuracy and KL divergence with the ground truth distribution for datasets with distinct variances of the number of segments (denoted as var.).

	$p(c\|v,n)$			$p(t\|v,n)$	
	C	M	B	R@0.3	R@0.5
Baseline	37.2	11.7	5.6	69.8	46.4
+ VidChain	**49.2**	**19.4**	**9.1**	**82.7**	**64.2**

Table 5: **Performance on $p(c|v,n)$ and $p(t|v,n)$ of CoTasks for $\mathcal{P}_{c\to t}$ and $\mathcal{P}_{t\to c}$ respectively.** Note that C, M, and B denote CIDEr, METEOR, and BLEU4, respectively, and R@k denotes Recall@k.

	Training Data ($\mathcal{D}_{\text{CT}}$)		Dense Video Captioning	
	$\mathcal{D}_{t\to c}$	$\mathcal{D}_{c\to t}$	SODA$_c$	METEOR
Baseline	✘	✘	7.2	7.7
CoTasks-$\mathcal{P}_{t\to c}$	✔	✘	7.4	7.6
	✔	✔	**7.5**	**8.3**
CoTasks-$\mathcal{P}_{c\to t}$	✘	✔	7.6	8.1
	✔	✔	**7.7**	**8.5**

Table 6: **Ablation study on data composition of $\mathcal{D}_{\text{CT}}$.**

	DVC		TVG	
	SODA$_c$	METEOR	R@0.3	mIoU
Baseline	7.7	8.5	60.2	41.9
$\mathcal{L}_{\text{DPO}}$	8.3	8.6	61.6	42.8
$\mathcal{L}_{\text{M-DPO}^-}$	8.6	**8.8**	62.4	43.4
$\mathcal{L}_{\text{M-DPO}}$ (ours)	**8.8**	**8.8**	**63.3**	**44.1**

Table 7: **Analysis on DPO objectives.** Note the baseline refers to VideoLLaMA2+CoTasks-$\mathcal{P}_{c\to t}$.

2017) to validate the effectiveness of our method. For implementation details and further details about the datasets and their metrics, refer to the supplement.

4.2 Main Results

We evaluate VidChain on the challenging Dense Video Captioning (DVC) and temporal video grounding (TVG) to verify the effectiveness of our approach in enhancing fine-grained video understanding. Note we report performances for both CoTasks paths, $\mathcal{P}_{c\to t}$ and $\mathcal{P}_{t\to c}$ for the DVC task.

Results. Tab. 1 demonstrates the effectiveness of the proposed VidChain by applying it on two state-of-the-art VideoLLMs, VTimeLLM and VideoLLaMA2. VidChain improves both VideoLLMs on two DVC benchmarks, ActivityNet and YouCook, thereby outperforming every VideoLLM. In detail, VideoLLaMA2+VidChain-$\mathcal{P}_{c\to t}$ shows a 22.2% gain in SODA$_c$ improving from 7.2 to 8.8, 14.3% gain in METEOR and 33.4% in CIDEr on ActivityNet. In YouCook2, the model shows an 45.5%, 60%, 93.5% increase for SODA$_c$, METEOR, and CIDEr, respectively.

Similar to the case of VideoLLaMA2, VidChain also shows consistent performance gains with VTimeLLM. For instance, VidChain boosts performance of VTimeLLM by up to 1.2, 1.4, and 6.9 points in SODA$_c$, METEOR, and CIDEr respectively on the YouCook benchmark for DVC, while it also outperforms the baseline in the ActivityNet in every metrics. Notably, VidChain applied to VTimeLLM with 7B LLM outperforms the baseline VTimeLLM with 13B LLM on every task by a large margin.

Moreover, Tab. 2 demonstrates the effectiveness of VidChain on TVG, where we show a prominent increase in performance when applied to both VideoLLMs. In particular, VTimeLLM+VidChain shows a 17.4, 16.0, 11.4, and 13.1 increase in Recall@0.3, Recall@0.5, Recall@0.7, and mIoU. In addition, we outperform the model further trained with the corresponding TVG datasets. The enhanced performance on TVG underlines the effectiveness of VidChain in enhancing the capability of a VideoLLM fine-grained video understanding, thereby also improving performance on a sub-task for DVC.

4.3 Quantitative Analysis

In the following experiments and analysis, we report results on ActivityNet for DVC using our best-performing model VideoLLaMA2+VidChain unless specified.

Effectiveness of CoTasks. In Tab. 3, we analyze the effectiveness of CoTasks. Results show that CoTasks yields consistent performance improvement on both VTimeLLM and VideoLLaMA2 regardless of the inference path ($\mathcal{P}_{t\to c}$ or $\mathcal{P}_{c\to t}$), compared to the baselines. In particular, when applied to VTimeLLM, CoTasks-$\mathcal{P}_{t\to c}$ shows 15.5% gain in SODA$_c$ for ActivityNet, and 20.6% gain in YouCook2. Moreover, we also observe consistent gains in TVG tasks by applying CoTasks, where the results are in the supplement. This result verifies the effectiveness of CoTasks in enhancing the reasoning capability of a VideoLLM.

Effectiveness of M-DPO. In Tab. 3, results of +VidChain are also reported, which denotes that M-DPO is also applied on top of CoTasks. Our results show that M-DPO generally improves performance on both VideoLLMs, VTimeLLM, and VideoLLaMA2. For instance, further training VideoLLaMA2+CoTasks-$\mathcal{P}_{c\to t}$ with M-DPO improves SODA$_c$, and METEOR by 1.1, and 0.3 points, as shown by the result of VideoLLaMA2+VidChain-$\mathcal{P}_{c\to t}$. Similarly, applying M-DPO consistently boosts performance on every VideoLLMs and benchmarks, showing its effectiveness.

Ablation studies on subtasks of CoTasks. We evaluate performances on three subtasks that compose CoTasks for

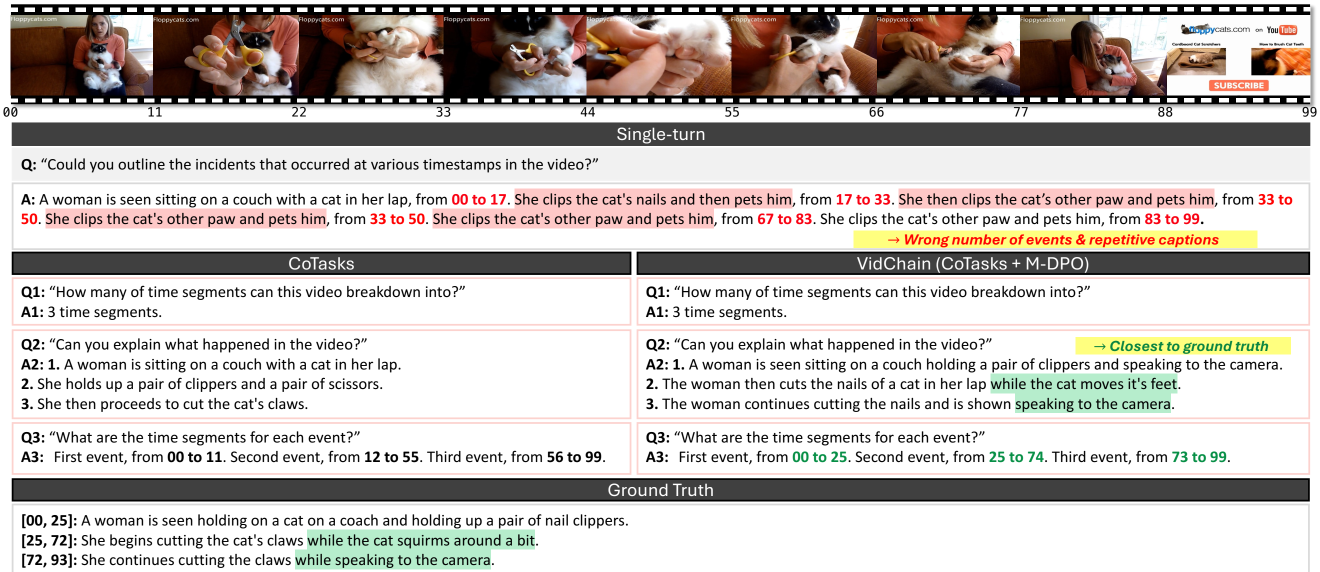


Figure 2: **Qualitative example of Dense Video Captioning.** Predictions of baseline VideoLLM (Single-turn), VideoLLM+CoTasks, and VidChain (CoTasks + M-DPO) are illustrated. Red and green highlights denote erroneous and accurate predictions, respectively. Visualization is done on ActivityNet validation set with VTimeLLM in $\mathcal{P}_{c\to t}$ path.

a detailed investigation: (1) time segment prediction $p(n|v)$, which is illustrated in the grey box in Fig. 1, (2) video paragraph captioning $p(c|v,n)$ of $\mathcal{P}_{c\to t}$, illustrated as the first red box and (3) temporal video segmentation $p(t|v,n)$ of $\mathcal{P}_{t\to c}$, illustrated as the first yellow box. As shown in both Tab. 4 and Tab. 5, among all subtasks, VidChain consistently achieves superior performance. Note for (1) we conduct experiment on two benchmark datasets with different variances of the number of segments in the video. For (3), we conducted experiment with the samples where both the baseline and VidChain accurately predicted the number of segments.

Ablation study on data composition of $\mathcal{D}_{\text{CT}}$. We conduct an ablation study on the effect of the inclusion of data with two paths for DVC, namely $\mathcal{D}_{t\to c}$ and $\mathcal{D}_{c\to t}$ in CoTasks training data $\mathcal{D}_{\text{CT}}$. The results are in Tab. 6, where including data with both paths is shown to perform better than using only a single type of path. We conjecture that two different paths are complementary to each other, therefore composing $\mathcal{D}_{\text{CT}}$ with data in both paths facilitates a VideoLLM's fine-grained video understanding capacity by letting a VideoLLM learn to solve the same objective in different ways.

Analysis on DPO objectives. In Tab. 7, we analyze different DPO objectives using our $\mathcal{D}_{\text{M-DPO}}$ dataset, where the optimization objective applied is only different. $\mathcal{L}_{\text{DPO}}$ (row 2) denotes that DPO is only applied to the final task instead of intermediate tasks and preference-gap aware DPO is not applied. Overall, it generally improves DVC performance, showing the effectiveness of the DPO approach in the DVC task. Still, additionally optimizing intermediate tasks with $\mathcal{L}_{\text{M-DPO}^-}$ (row 3) enables additional gains of 0.3, and 0.2 over $\mathcal{L}_{\text{DPO}}$ (row 2) in SODA$_c$, and METEOR. Finally, applying the preference gap-aware M-DPO ($\mathcal{L}_{\text{M-DPO}}$) results in the best performance (row 4). The ablation results show the effectiveness of M-DPO components. A more detailed explanation, *e.g.*, DPO margin for each method across training iteration, is in the supplement.

4.4 Qualitative Analysis

Fig. 2 compares qualitative results of a baseline VideoLLM (single-turn) with one trained using CoTasks and VidChain (CoTasks + M-DPO). As illustrated, baseline VideoLLM shows inferior performance on DVC, segmenting a video into an overly large number of events (6 predicted vs. 3 ground-truth), while captions for each event are also highly repetitive ("She clips the cat's other paw and pets him"), revealing the lack of a baseline in the capability of fine-grained video understanding. In contrast, a VideoLLM trained with CoTasks successfully segments a video into three events, while captions for each segment are more distinctive, showing the effectiveness in breaking down complex DVC into sub-tasks. Moreover, further aligning the model with M-DPO yields the best results, closely matching ground-truths and showcasing M-DPO's metric-aligned supervision.

5 Conclusion

In this paper, we propose a framework, VidChain, comprised of the Chain-of-Tasks (CoTasks), and Metric-based Direct Preference Optimization (M-DPO). CoTasks decompose the complicated task into a series of sub-tasks, easing the difficulties in solving the task. M-DPO aligns a VideoLLM with evaluation metrics of sub-tasks, providing supervision aligned with the abilities required for those tasks. Applied on two different VideoLLMs, VidChain enhances fine-grained understanding of models, consistently improving their performance thereby outperforming previous VideoLLMs.

Acknowledgments

This work was partly supported by the National Supercomputing Center with supercomputing resources including technical support (KSC-2023-CRE-0185, 25%), and Institute of Information & Communications Technology Planning & Evaluation (IITP) grants funded by the Korea government (MSIP & MSIT) (No. RS-2024-00443251, 25%, Accurate and Safe Multimodal, Multilingual Personalized AI Tutors; No. RS-2024-00457882, 25%, National AI Research Lab Project; No. IITP-2024-RS-2024-00436857, 25%, Information Technology Research Center ITRC).

References

Ahn, D.; Choi, Y.; Yu, Y.; Kang, D.; and Choi, J. 2024. Tuning large multimodal models for videos using reinforcement learning from ai feedback. In *ACL*.

Banerjee, S.; and Lavie, A. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In *ACL*.

Chen, Z.; Wu, J.; Wang, W.; Su, W.; Chen, G.; Xing, S.; Zhong, M.; Zhang, Q.; Zhu, X.; Lu, L.; et al. 2024. Internvl: Scaling up vision foundation models and aligning for generic visual-linguistic tasks. In *CVPR*.

Cheng, Z.; Leng, S.; Zhang, H.; Xin, Y.; Li, X.; Chen, G.; Zhu, Y.; Zhang, W.; Luo, Z.; Zhao, D.; et al. 2024. VideoLLaMA 2: Advancing Spatial-Temporal Modeling and Audio Understanding in Video-LLMs. arXiv:2406.07476.

Christiano, P. F.; Leike, J.; Brown, T.; Martic, M.; Legg, S.; and Amodei, D. 2017. Deep reinforcement learning from human preferences. In *NeurIPS*.

Dai, W.; Li, J.; Li, D.; Tiong, A.; Zhao, J.; Wang, W.; Li, B.; Fung, P.; and Hoi, S. 2023. Instructblip: Towards general-purpose vision-language models with instruction tuning. In *NeurIPS*.

Fujita, S.; Hirao, T.; Kamigaito, H.; Okumura, M.; and Nagata, M. 2020. SODA: Story oriented dense video captioning evaluation framework. In *ECCV*.

Gunjal, A.; Yin, J.; and Bas, E. 2024. Detecting and preventing hallucinations in large vision language models. In *AAAI*.

Huang, B.; Wang, X.; Chen, H.; Song, Z.; and Zhu, W. 2024. Vtimellm: Empower llm to grasp video moments. In *CVPR*.

Kim, M.; Kim, H. B.; Moon, J.; Choi, J.; and Kim, S. T. 2024. Do You Remember? Dense Video Captioning with Cross-Modal Memory Retrieval. In *CVPR*.

Ko, D.; Lee, J. S.; Choi, M.; Chu, J.; Park, J.; and Kim, H. J. 2023a. Open-Vocabulary Video Question Answering: A New Benchmark for Evaluating the Generalizability of Video Question Answering Models. In *ICCV*.

Ko, D.; Lee, J. S.; Kang, W.; Roh, B.; and Kim, H. J. 2023b. Large language models are temporal and causal reasoners for video question answering. In *EMNLP*.

Krishna, R.; Hata, K.; Ren, F.; Fei-Fei, L.; and Carlos Niebles, J. 2017. Dense-captioning events in videos. In *ICCV*.

Lai, X.; Tian, Z.; Chen, Y.; Yang, S.; Peng, X.; and Jia, J. 2024. Step-DPO: Step-wise Preference Optimization for Long-chain Reasoning of LLMs. arXiv:2406.18629.

Li, K.; He, Y.; Wang, Y.; Li, Y.; Wang, W.; Luo, P.; Wang, Y.; Wang, L.; and Qiao, Y. 2023. Videochat: Chat-centric video understanding. arXiv:2305.06355.

Li, K.; Wang, Y.; He, Y.; Li, Y.; Wang, Y.; Liu, Y.; Wang, Z.; Xu, J.; Chen, G.; Luo, P.; et al. 2024. Mvbench: A comprehensive multi-modal video understanding benchmark. In *CVPR*.

Lin, B.; Zhu, B.; Ye, Y.; Ning, M.; Jin, P.; and Yuan, L. 2023. Video-llava: Learning united visual representation by alignment before projection.

Liu, H.; Li, C.; Li, Y.; and Lee, Y. J. 2024. Improved baselines with visual instruction tuning. In *CVPR*.

Liu, H.; Li, C.; Wu, Q.; and Lee, Y. J. 2023. Visual instruction tuning. In *NeurIPS*.

Maaz, M.; Rasheed, H.; Khan, S.; and Khan, F. S. 2024. Video-chatgpt: Towards detailed video understanding via large vision and language models. In *ACL*.

Ouyang, L.; Wu, J.; Jiang, X.; Almeida, D.; Wainwright, C.; Mishkin, P.; Zhang, C.; Agarwal, S.; Slama, K.; Ray, A.; et al. 2022. Training language models to follow instructions with human feedback. In *NeurIPS*.

Qian, L.; Li, J.; Wu, Y.; Ye, Y.; Fei, H.; Chua, T.-S.; Zhuang, Y.; and Tang, S. 2024. Momentor: Advancing video large language model with fine-grained temporal reasoning. In *ICML*.

Rafailov, R.; Sharma, A.; Mitchell, E.; Manning, C. D.; Ermon, S.; and Finn, C. 2023. Direct preference optimization: Your language model is secretly a reward model. In *NeurIPS*.

Ren, S.; Yao, L.; Li, S.; Sun, X.; and Hou, L. 2024. Timechat: A time-sensitive multimodal large language model for long video understanding. In *CVPR*.

Song, F.; Yu, B.; Li, M.; Yu, H.; Huang, F.; Li, Y.; and Wang, H. 2024. Preference ranking optimization for human alignment. In *AAAI*.

Vedantam, R.; Lawrence Zitnick, C.; and Parikh, D. 2015. Cider: Consensus-based image description evaluation. In *CVPR*.

Wang, T.; Zhang, R.; Lu, Z.; Zheng, F.; Cheng, R.; and Luo, P. 2021. End-to-end dense video captioning with parallel decoding. In *ICCV*.

Xu, H.; Sharaf, A.; Chen, Y.; Tan, W.; Shen, L.; Van Durme, B.; Murray, K.; and Kim, Y. J. 2024. Contrastive preference optimization: Pushing the boundaries of llm performance in machine translation. In *ICML*.

Yang, A.; Nagrani, A.; Laptev, I.; Sivic, J.; and Schmid, C. 2024. Vidchapters-7m: Video chapters at scale. In *NeurIPS*.

Yang, A.; Nagrani, A.; Seo, P. H.; Miech, A.; Pont-Tuset, J.; Laptev, I.; Sivic, J.; and Schmid, C. 2023. Vid2seq: Large-scale pretraining of a visual language model for dense video captioning. In *CVPR*.

Ye, Q.; Xu, H.; Ye, J.; Yan, M.; Hu, A.; Liu, H.; Qian, Q.; Zhang, J.; and Huang, F. 2024. mplug-owl2: Revolutionizing multi-modal large language model with modality collaboration. In *CVPR*.

Yu, T.; Yao, Y.; Zhang, H.; He, T.; Han, Y.; Cui, G.; Hu, J.; Liu, Z.; Zheng, H.-T.; Sun, M.; et al. 2024. Rlhf-v: Towards trustworthy mllms via behavior alignment from fine-grained correctional human feedback. In *CVPR*.

Yuan, L.; Cui, G.; Wang, H.; Ding, N.; Wang, X.; Deng, J.; Shan, B.; Chen, H.; Xie, R.; Lin, Y.; et al. 2024. Advancing llm reasoning generalists with preference trees. arXiv:2404.02078.

Zhang, H.; Li, X.; and Bing, L. 2023. Video-llama: An instruction-tuned audio-visual language model for video understanding. In *EMNLP-Demo*.

Zhou, L.; Xu, C.; and Corso, J. 2018. Towards automatic learning of procedures from web instructional videos. In *AAAI*.

Zhou, X.; Arnab, A.; Buch, S.; Yan, S.; Myers, A.; Xiong, X.; Nagrani, A.; and Schmid, C. 2024. Streaming dense video captioning. In *CVPR*.

Zhu, B.; Lin, B.; Ning, M.; Yan, Y.; Cui, J.; Wang, H.; Pang, Y.; Jiang, W.; Zhang, J.; Li, Z.; et al. 2024. Language-Bind: Extending Video-Language Pretraining to N-modality by Language-based Semantic Alignment. In *ICLR*.

Zhu, X.; Su, W.; Lu, L.; Li, B.; Wang, X.; and Dai, J. 2021. Deformable detr: Deformable transformers for end-to-end object detection. In *ICLR*.