IMAGECHAIN: Advancing Sequential Image-to-Text Reasoning in Multimodal Large Language Models

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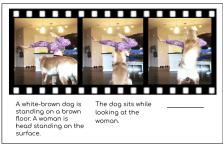
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Abstract

Reasoning over sequences of images remains a challenge for multimodal large language models (MLLMs). While recent models incorporate multi-image data during pre-training, they still struggle to recognize sequential structures, often treating images independently. This work introduces IMAGECHAIN, a framework that enhances MLLMs with sequential reasoning capabilities over image data by modeling visual sequences as a multi-turn conversation. In IMAGECHAIN, images are interleaved with corresponding textual descriptions to form a controlled dialogue that explicitly captures temporal dependencies and narrative progression. Our method optimizes for the task of next-scene description, where the model generates a context-aware description of an upcoming scene based on preceding visual and textual cues. We demonstrate that our approach improves performance on the nextscene description task – achieving an average improvement from 3.7% to 19% in SimRate, a metric that quantifies semantic similarity to human-annotated ground truths. Moreover, IM-AGECHAIN achieves robust zero-shot out-ofdomain performance in applications ranging from comics to robotics. Extensive experiments validate that instruction-tuning in a multimodal, multi-turn conversation design is key to bridging the gap between static image understanding and temporally-aware reasoning.¹

1 Introduction

Multimodal large language models (MLLMs) such as GPT-4V (Achiam et al., 2023), MM1 (McK-inzie et al., 2025), and LLaVA-NeXT (Liu et al., 2024) have demonstrated impressive reasoning capabilities by integrating text and image inputs, advancing the state of visual-language understanding (Zhang et al., 2024a). Standard tasks like image



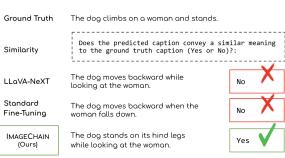


Figure 1: Illustration of the proposed *next-scene description* task. Models and techniques that process images independently, such as LLaVA-NeXT and standard finetuning, fail to capture the correct progression, leading to errors. In contrast, IMAGECHAIN explicitly models sequences as multi-turn conversations, enabling it to generate a more accurate description, closely aligning with the human-annotated ground truth.

captioning and visual question answering (VQA) have driven significant progress in recognizing objects, attributes, and their relationships within individual images (Stefanini et al., 2022; Srivastava et al., 2021; Narins et al., 2024; Wang, 2022). However, many real-world applications such as storytelling (Huang et al., 2016; Wang et al., 2020; Liu et al., 2023), event comprehension (Lei et al., 2020; Cheng et al., 2024), and robotics (O'Neill et al., 2024), demand a deeper understanding of temporal and narrative progression across sequences of images.

Recent methods have extended MLLMs such as LLaVA-NeXT, Mantis (Jiang et al., 2024a), and Qwen2-VL (Wang et al., 2024b) to handle multi-

¹Code, dataset, and checkpoints are publicly available at https://github.com/danaesavi/ImageChain.

image inputs. However, they typically process images independently or summarize entire scenes, rather than explicitly modeling the evolution of events over time. In contrast, *sequential image reasoning* requires a model to capture dependencies across frames to predict future actions. Figure 1 illustrates our proposed task, *next-scene description*, which consists of generating a text description of a visual scene based on a sequence of preceding frames and their corresponding descriptions – a challenge that existing models, such as LLaVA-NeXT, have yet to overcome.

To address this gap, we introduce IMAGECHAIN, an efficient framework that provides MLLMs with explicit sequential reasoning capabilities. By reformulating a visual sequence as a multi-turn conversation, IMAGECHAIN interleaves images with their corresponding text descriptions to build a sequential context for generating the next-scene description. Our approach achieves substantial improvements on similarity rate (SimRate), a metric that quantifies semantic similarity to human-annotated ground truths, across both in-domain and out-ofdomain tasks using only approximately 4,000 training samples. To support our method, we repurpose StoryBench (Bugliarello et al., 2023), a video dataset with human-annotated descriptions, to create and introduce StoryFrames - a high-quality, temporally coherent corpus tailored towards sequential image-text reasoning across different context lengths. StoryFrames provides annotated samples that enable IMAGECHAIN to efficiently adapt and learn robust temporal dependencies with minimal data. Our contributions are as follows:

- **Framework:** We introduce IMAGECHAIN, an image-to-text reasoning adaptation framework that models image sequences as multiturn conversations for generating *next-scene descriptions*, achieving an overall SimRate of 19% versus 3.7% for standard MLLMs.
- Robust Out-of-Domain Performance: In robotics, IMAGECHAIN achieves an F1 score of 27.1—almost double the 14.4 of standard fine-tuning along with gains in structured settings such as comics.
- Context Length Ablations: We show that training across multiple context lengths consistently outperforms training on single length, suggesting that exposure to varied temporal spans enhances sequential reasoning.

• StoryFrames: We repurpose StoryBench, a video dataset with human-annotated descriptions, into StoryFrames, a corpus of 8,881 samples for facilitating research on general-purpose paired sequential vision and text data.

2 Related Work

2.1 Evolution of Sequential Visual Reasoning

Visual storytelling emerged as an early effort to generate coherent narratives from image sequences (Huang et al., 2016). Initial approaches relied on convolutional neural networks (LeCun et al., 1995) for visual feature extraction paired with recurrent neural networks (Hochreiter, 1997) for narrative generation (Gonzalez-Rico and Fuentes-Pineda, 2018; Kim et al., 2018). Although these methods demonstrated that visual and textual information could be integrated to produce compelling stories, they relied on overly broad scene summarization techniques (Hong et al., 2020; Wang et al., 2020), rather than explicitly modeling the temporal dependencies required to predict future events.

With the introduction of MLLMs such as GPT-4V (Achiam et al., 2023), MM1 (McKinzie et al., 2025), and LLaVA-NeXT (Liu et al., 2024), significant progress has been made in static image understanding for tasks like image captioning and visual question answering (Liu et al., 2023; Lin and Chen, 2024; Zhang et al., 2025b). Despite these successes, many MLLMs remain optimized for static or non-sequential multi-image inputs, limiting their ability to capture temporal dynamics. This limitation motivates our work to develop a method that explicitly models temporal dependencies across image sequences.

2.2 Challenges in Context Length and Generalization

A critical challenge in sequential visual reasoning lies in effectively handling variable-length temporal contexts (Zhou et al., 2024b). Many existing models are trained on short or fixed-length sequences and thus struggle when presented with complex temporal spans or variable length contexts (Thawakar et al., 2025). Furthermore, models show particular difficulties handling subtle temporal dependencies and structured event progressions where actions follow constrained logical sequences, such as in comics or robotics (Wang et al., 2024c). A recent analysis suggests that MLLMs rely on surface-level cues (Zhou et al., 2024b),

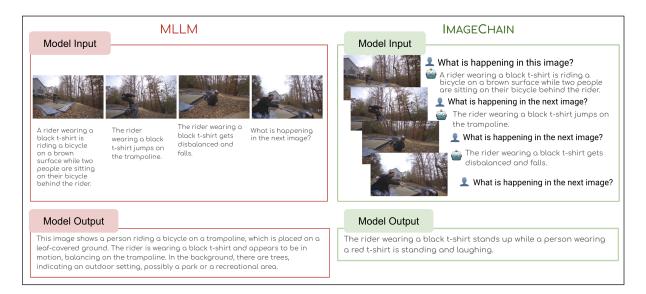


Figure 2: Comparison of multi-image sequential reasoning between a standard Multimodal Large Language Model (MLLM) and our proposed model IMAGECHAIN. The left side shows the output of MLLM, which fails to accurately describe the next event in the image sequence. The right side presents IMAGECHAIN, an image-to-text reasoning adaptation framework that models image sequences as multi-turn conversations, enabling a more accurate and temporally aware description of the next scene.

leading to performance degradation when processing extended contexts or adapting to novel scenarios (Imam et al., 2025). These challenges underscore the need for approaches that capture variable-range temporal dependencies and generalize more robustly across diverse domains.

2.3 Instruction Tuning Over Multi-Turn Conversations

Instruction tuning (Sanh et al., 2022; Wei et al., 2022) enhances LLMs by improving their ability to follow general task-agnostic directives while requiring limited training data (Zhou et al., 2024a). This methodology diverges from conventional finetuning approaches by exposing the model to varied instructional formulations, which ensures that the emphasis lies on adhering to directives rather than on task-specific details. (Zhang et al., 2024b). Empirical evaluations demonstrate that instruction-tuned variants consistently outperform competing baselines in output quality across open-ended (Jha et al., 2023), knowledge (Jiang et al., 2024b), and reasoning (Tang et al., 2024) tasks.

Instruction tuning over multi-turn conversations extend this approach by introducing sequential dependencies between interactions, where each turn builds on prior user-model exchanges (Zhang et al., 2025a). Despite these advances in LLMs, such multi-turn conversational techniques have not yet been applied to multimodal settings.

IMAGECHAIN extends the multi-turn conversational paradigm to MLLMs for improved sequential visual reasoning by leveraging the strengths of instruction tuning and multi-turn interactions for integrating sequential visual data. Rather than relying on emerging user-model interactions, we explicitly structure the conversation as a fixed sequence (Wang et al., 2024a). We interleave visual embedding tokens with scene descriptions to build a controlled context that emphasizes temporal dependencies. Each turn poses a targeted question about an upcoming scene, with the expected response being a text description. We call this task next-scene description (Figure 2), where the goal is to generate an accurate description of a visual scene based on preceding frames and annotations.

3 IMAGECHAIN: Optimizing MLLMs for Sequential Image-to-Text Reasoning

IMAGECHAIN enhances an MLLM's ability to reason over sequential image data by optimizing the task of *next-scene description*. We assume a multimodal language model that can process both text and visual features.

3.1 Problem Setup

Let S be a story represented as a sequence of scenes $S = \langle s_t \rangle_{t=1}^T$. Each scene s consists of a sequence of frames $V = \langle v_k \rangle_{k=1}^K$ and a textual description D that corresponds to the entire scene, expressed

```
<s> USER: What is happening in this image? <Image></Image></Image>
ASSISTANT: A rider wearing a black t-shirt is riding a bicycle on a brown surface while two people are sitting on their bicycle behind the rider. </s>
<s> USER: What is happening in the next image? <Image></image></image></s>
ASSISTANT: The rider wearing a black t-shirt jumps on the trampoline. </s>
<s> USER: What is happening in the next image? <Image></image></image></image></s>
ASSISTANT: The rider wearing a black t-shirt gets disbalanced and falls. </s>
<s> USER: What is happening in the next image? <Image></image></image></s>
ASSISTANT:
```

Figure 3: Multi-turn conversation design for a story with four scenes, where each turn corresponds to a scene. A turn begins with a user question and ends with the assistant's response. The context includes three completed turns (i.e., three scenes), along with the next user question and the corresponding visual cue, which are used to generate the *next-scene description*.

as s = (V, D). The number of scenes in a story and the number of frames per scene can vary across different stories.

3.2 Obtaining Visual Scene Representations

Each sequence of frames V is transformed into a fixed-size representation to be paired with the sole description D. Given a visual encoder $f_{\theta}(\cdot)$, each frame v_k is mapped to a feature vector as $z_k = f_{\theta}(v_k)$, where $z_k \in \mathbb{R}^d$.

We then average the feature vectors z_k over all frames to compute the scene-level visual representation as follows: $\bar{V} = \frac{1}{K} \sum_{k=1}^K z_k$. The averaged feature vector \bar{V} serves as a fixed-size summary of the visual content in V, which is then paired with the corresponding textual description D.

3.3 Multi-Turn Conversation Construction

To capture the sequential nature of each story, we frame every scene as part of a multi-turn conversation between the user and the model. For a given story S, let $\tau \in \{1,2,\ldots,T\}$ denote the turns, where each turn τ is a triple $(Q_{\tau},\bar{V}_{\tau},D_{\tau})$. Q_{τ} is a predefined question string that asks from a user perspective "What is happening in this image?" if $\tau=1$ to start the conversation, or "What is happening in the next image?" for all $\tau>1$ to proceed to the next turn in the conversation. Therefore, each story S can be represented by a conversation context C of T turns:

$$C = \langle (Q_1, \bar{V}_1, D_1), \dots, (Q_T, \bar{V}_T, D_T) \rangle.$$
 (1)

3.4 Instruction Fine-Tuning Objective

We fine-tune the model using standard supervised next-token prediction over the multi-turn conversation context C. Let $W_C = \langle w_1, w_2, \dots, w_N \rangle$ denote the concatenated sequence of all text tokens

in the context C. Our training goal for an individual story is to minimize the cross-entropy loss over all text tokens w_i conditioned on all preceding text tokens and the visual context:

$$\mathcal{L}_{IC} = -\sum_{i=1}^{N} \log p\left(w_i \mid w_{1:i-1}, \{\bar{V}_{\tau}\}_{\tau=1}^{T}\right). \quad (2)$$

The visual embeddings \bar{V} are provided only for conditioning and do not contribute to the loss. By enforcing a multi-turn structure that explicitly exposes the model to sequential context at each turn, minimizing \mathcal{L}_{IC} improves the model's temporal reasoning over sequential image data.

3.5 Next-Scene Description Generation

To generate the next-scene description \hat{D}_{τ} at turn τ , we condition the instruction-tuned model on the completed turns $\{1,2,\ldots,\tau-1\}$, plus the current question Q_{τ} and the embedding \bar{V}_{τ} . Note that the next-scene description D_{τ} is withheld:

$$C_{\tau} = \left\langle (Q_1, \, \bar{V}_1, \, D_1), \, \dots, \, (Q_{\tau-1}, \, \bar{V}_{\tau-1}, \, D_{\tau-1}), \, (Q_{\tau}, \, \bar{V}_{\tau}, \, \Box) \right\rangle.$$
 (3)

At inference time, the model auto-regressively generates the next-scene description \hat{D}_{τ} based on the provided multi-turn context C_{τ} . An example context with $\tau=4$ turns is illustrated in Figure 3.

4 The StoryFrames Dataset

We adapt the StoryBench dataset (Bugliarello et al., 2023) to create *StoryFrames* – a dataset specifically designed for the *next-scene description* task on sequential visual reasoning. StoryFrames repurposes human-annotated temporal segments from three distinct sources: Oops (Epstein et al., 2020), which

captures unexpected actions; DiDeMo (Anne Hendricks et al., 2017), which provides event grounding through natural language; and UVO (Wang et al., 2021), which focuses on object-centric reasoning in video sequences. In this dataset, each story represents a single "sample" consisting of a sequence of scenes. Every scene is defined by human-annotated start and end points, accompanied by a textual description covering its duration. Each scene is further divided into multiple extracted frames, forming a hierarchical structure that supports detailed sequential reasoning.

Frame Extraction. To extract frames, we implement an adaptive frame sampling strategy that adjusts the number of frames based on the total duration of each story. For stories up to 5 seconds, we extract 8 frames; for 5 to 10 seconds, 12 frames; for 10 to 15 seconds, 15 frames; for 15 to 30 seconds, 20 frames; and for stories exceeding 30 seconds, 25 frames. This approach ensures broad temporal coverage while maintaining manageable computational requirements. Moreover, to preserve narrative continuity and prevent overlap between adjacent scenes, a 0.2-second temporal offset is introduced between consecutive action segments.

Frame Allocation Across Scenes. Within each story, frame allocation to individual scenes is performed proportionally to the duration of each scene, while ensuring that every scene receives at least two frames. Formally, for a scene s with duration m_s in a story S of total duration M and given a total frame budget F, the number of frames allocated is computed as follows: $K_s = \max\left(2, \left|\frac{m_s}{M} \cdot F\right|\right)$.

StoryFrames Organization. StoryFrames comprises 8,881 sequences and is organized into distinct subsets based on the number of scenes per story (Figure 4) to enable evaluation of models across varying context lengths and complexity.

Dataset Splits. For sequences containing 2 to 7 scenes, we maintain an 80-20 train-validation split, while single-scene sequences and those with 8 or more scenes are reserved for further validation to assess generalization to extreme cases. Figure 4 visualizes the dataset distribution.

5 Experimental Setup

5.1 Models

We evaluate a series of model configurations ranging from unmodified baselines to fully fine-tuned

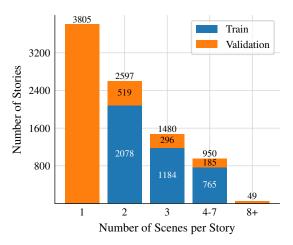


Figure 4: Distribution of scenes in our introduced StoryFrames dataset. A *story* corresponds to one "sample", whereas multiple *scenes* make up one story.

variants. This systematic evaluation allows us to isolate the contributions of fine-tuning, visual context, and structured dialogue, thereby assessing the necessity and effectiveness of IMAGECHAIN.

MLLM: The baseline MLLM, designed to assess task performance without any task-specific modifications.

MLLM-ICL: An in-context learning baseline that receives three demonstrations of the task, designed to evaluate whether sequential image reasoning can be learned solely through seeing examples.

MLLM-FT: MLLM with standard fine-tuning on the StoryFrames dataset, allowing a direct comparison with our proposed method.

VisualContext: A variant fine-tuned using only the visual context from preceding actions, i.e., all textual descriptions are omitted, enabling us to assess the contribution of text in the prediction task.

FinalScene: A variant that represents image captioning by fine-tuning the model to predict the next description based solely on the final visual action, designed to analyze whether incorporating context improves performance.

IMAGECHAIN-NoFT: Our approach that employs a multi-turn conversation structure but without any fine-tuning, isolating the effect of prompting with the structured dialogue format.

IMAGECHAIN: The complete method that integrates multi-turn prompting with fine-tuning on StoryFrames, explicitly modeling sequential dependencies to enhance *next-scene descriptions*.

5.2 Dataset and Context Length Splits

To evaluate the impact of temporal context on generating *next-scene descriptions*, we use stories from

the StoryFrames dataset with 2 to 7 scenes. In our setup, the model is given a varying number of preceding scenes to predict the textual description for the current one. This analysis reflects real-world applications that require reasoning over differing lengths of context. We define 3 evaluation settings:

C2: The model uses one preceding scene (a total of 2 scenes, including the current one).

C3: Here, the model uses two preceding scenes (totaling 3 scenes).

C4–7: In this setting, the model receives a longer sequence, with three to six preceding scenes (corresponding to sequences of 4 to 7 scenes in total).

C2–7: The model is exposed to the full range of context lengths available (i.e., from 2 to 7 scenes). This range captures both short-term dependencies and more extended temporal structures and is designed to improve the model's ability to generalize across varying context lengths.

By comparing model performance across the fixed settings (C2, C3, C4–7, C2–7), we are able to isolate the contribution of context length to *next-scene description* and provide insights on optimizing for specific context lengths.

5.3 Training and Implementation Details

All of our model configurations share a common experimental backbone based on LLaVA-v1.6-Vicuna-7B (Liu et al., 2024), which aligns Vicuna (Chiang et al., 2023) and CLIP (Radford et al., 2021) into an MLLM. We fine-tune the models using low-rank adaptation (Hu et al., 2021, LoRA) in combination with DeepSpeed ZeRO-3, running approximately 1-2 hours per model on 8 NVIDIA A100 GPUs. The baseline training is conducted over 3 epochs on the StoryFrames dataset with a per-device batch size of 4 and gradient accumulation of 1. LoRA is configured with a rank r = 128and $\alpha = 256$. A learning rate of 2×10^{-5} is applied, with a cosine learning rate schedule and a warmup ratio of 3%. For optimization, the adaptive momentum optimizer with decoupled weight decay (Loshchilov and Hutter, 2019) is used. For IMAGECHAIN trained on C2 and C3 we adjust the number of training epochs to 5, and to 7 epochs when trained on C4–7 due to the smaller training sample sizes. All other training settings remain unchanged.

5.4 Evaluation

LLM-as-a-Judge. To quantitatively assess the quality of the generated descriptions, we use sim-

ilarity rate (**SimRate**), an adapted version of win rate (Chiang et al., 2024), as a metric. Given the inherent variability in how visual events can be described literally, conventional metrics relying on n-gram overlap are inadequate for capturing semantic equivalence (Culy and Riehemann, 2003; Bulian et al., 2022). Instead, we follow recent literature (Li et al., 2024, 2025) and adopt LLMs as evaluators (Eldan and Li, 2023). For our generated next-scene description D_{τ} , Llama 3 70B (Dubey et al., 2024) determines whether or not it conveys a similar meaning to the ground truth scene description D_{τ} , effectively serving as a proxy for human evaluators (Li et al., 2023; Chiang et al., 2024). The prompt used for this framework is detailed in Appendix A. The overall SimRate follows as the fraction of comparisons where model-generated descriptions are judged semantically similar to the human-annotated ground truth descriptions.

Out-of-Domain Generalization. To further assess model generalization, we evaluate performance on several out-of-domain datasets that target diverse sequential reasoning challenges. Specifically, we test on three datasets derived from the Mementos benchmark (Wang et al., 2024c). **Comics**, which features wordless multi-panel comics; **Daily-Life (DL)** (Xiao et al., 2021), consisting of videos depicting everyday activities; and **Robo** (O'Neill et al., 2024), which contains robotics tasks. For evaluation, behavioral cues, (e.g., key verbs or verb phrases, are extracted from generated descriptions using GPT-4V (Achiam et al., 2023) and compared against human annotations using F1 score.².

6 Results

Explicit Sequence Modeling Improves Temporal Reasoning. Table 1 shows that our proposed IMAGECHAIN model consistently achieves the highest SimRate across all evaluated context lengths, demonstrating the value of explicitly modeling a sequence of images for *next-scene description* task. IMAGECHAIN significantly outperforms standard fine-tuning (MLLM-FT), with a notable 15.39 percentage point improvement in SimRate on C6, the longest evaluated context length. Additionally, IMAGECHAIN achieves 19.02% on C2-6, surpassing VisualContext (13.01%) and FinalScene (9.71%), underscoring the value of incorporating both images and textual description history. Even with-

 $^{^2}$ We follow Mementos evaluation setup (Wang et al., 2024c).

Model	C2	С3	C4	C5	C6	C4-6	C2-6
MLLM	5.20	2.36	1.67	1.92	0.00	1.58	3.70
MLLM-ICL	0.19	0.34	0.00	0.00	0.00	0.00	0.20
MLLM-FT	18.11	19.59	15.83	3.85	15.38	12.13	17.52
VisualContext	12.52	16.22	11.67	1.92	15.38	8.96	13.01
FinalScene	9.63	10.47	11.67	1.92	7.69	8.44	9.71
IMAGECHAIN-NoFT	6.94	6.08	12.50	0.00	15.38	8.96	7.11
IMAGECHAIN	18.30	21.28	19.17	9.62	30.77	16.87	19.02

Table 1: Similarity Rate (SimRate, %) across varying evaluation context lengths for IMAGECHAIN and baseline models trained on C2-7. IMAGECHAIN consistently outperforms all baselines and achieves the highest SimRate across all evaluated contexts.

Model	Test	SimRate	A
$IMAGECHAIN_{C2}$	C2	16.6	-
$IMAGECHAIN_{C2-7}$	C2	18.3	▲ 1.7
$IMAGECHAIN_{C3}$	C3	16.2	-
$IMAGECHAIN_{C2-7}$	C3	21.3	▲ 5.1
$IMAGECHAIN_{C4-7}$	C4-6	14.0	-
$IMAGECHAIN_{C2-7}$	C4-6	16.8	▲ 2.8

Table 2: Similarity rate (SimRate) on *next-scene description* when IMAGECHAIN is trained and evaluated on varying context lengths. \triangle refers to the gains from training on $C\tau$ -7 compared to the corresponding $C\tau$ trained model. IMAGECHAIN benefits from training on different context lengths (i.e., number of scenes).

out fine-tuning, IMAGECHAIN-NoFT outperforms MLLM on C2-6 (7.11% vs. 3.70%), demonstrating the benefits of explicitly modeling image sequences. However, fine-tuning remains essential for optimal performance, suggesting that MLLMs lack strong inherent temporal reasoning skills without additional training.

IMAGECHAIN Benefits from Training on Different Context Lengths. We train and evaluate an IMAGECHAIN model for each context length, with results shown in Table 2. We observe that IMAGECHAIN $_{C2-7}$ model outperforms the baseline IMAGECHAIN $_{C2}$ model when tested on C2, achieving a 1.7 point improvement in SimRate (18.3% vs. 16.6%). This suggests that training on a broader range of context lengths helps the model generalize better, even when predicting in shorter contexts. Similarly, we find that IMAGECHAIN $_{C2-7}$, which is trained on the entire range of temporal spans, consistently outperforms models trained on specific context lengths. This suggests that training across multiple context lengths enables robust se-

quential reasoning. Additionally, when tested on C3, IMAGECHAIN $_{C2-7}$ demonstrates a substantial improvement of 5.1 points (21.3% vs. 16.2%) over the baseline IMAGECHAIN $_{C3}$ model. Finally, on the C4-6 test setting, IMAGECHAIN $_{C2-7}$, achieves a 2.8 point increase in SimRate (16.8% vs. 14%). This indicates that the sequential training strategy across multiple context lengths enables stronger reasoning over extended visual sequences.

Training on Longer Contexts Improves Sequen**tial Reasoning.** Figure 5 shows the models performance for fine-tuned models trained on different context lengths. IMAGECHAIN achieves the highest overall SimRate when evaluated on C2-6, particularly when trained on longer contexts, reaching 13.6% when trained on C4-7. This surpasses other models, such as MLLM-FT, which achieves 9.8% under the same training conditions. MLLM-FT excels in short contexts but struggles with longer dependencies, suggesting limitations in handling extended sequences without explicit sequence modeling. VisualContext, underperforms on longer sequences (7.7% trained on C4-7 and evaluated on C6), highlighting the benefit of including text descriptions for fine-tuning in long contexts.

6.1 Out-of-domain Setup

Table 3 compares IMAGECHAIN with various baselines and large-scale multimodal models (GPT-4V, Gemini (Gemini Team et al., 2023)) across different domains. While GPT-4V and Gemini achieve the highest F1 scores, they operate at a much larger parameter and training data scale compared to our models, making direct comparisons challenging, but serve as a reference.

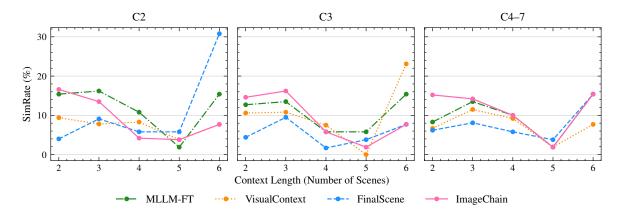


Figure 5: Model performance (SimRate) for fine-tuned models trained on different context lengths (C2, C3, C4-7). IMAGECHAIN achieves the highest overall SimRate when trained on long contexts (C4-7).

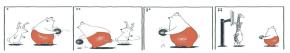
Comics	DL	Robo
18.1	33.6	34.0
16.3	21.6	39.4
13.3	23.5	15.2
13.0	18.4	14.4
11.2	18.3	27.8
13.4	26.5	19.0
16.2	20.8	27.1
	18.1 16.3 13.3 13.0 11.2 13.4	18.1 33.6 16.3 21.6 13.3 23.5 13.0 18.4 11.2 18.3 13.4 26.5

Table 3: Zero-shot out-of-domain performance comparison (F1 score) on Comics, Daily-Life (DL), and Robotics (Robo) datasets. IMAGECHAIN excels in structured, event-based reasoning tasks (comics and robotics), trailing Gemini only by 0.1 and 0.8 points, respectively. GPT-4V and Gemini results are taken from Wang et al. (2024c).

Comics. In the comics domain, IMAGECHAIN trails Gemini by only 0.1 points (16.2 vs. 16.3) and surpasses all 7B baselines, indicating that modeling sequential dependencies benefits structured visual narratives. Figure 6 shows how IMAGECHAIN captures the evolution of events over time, unlike MLLM-FT that focus on static observations.

Daily-Life. For daily life (DL) videos, IM-AGECHAIN lags behind FinalScene (20.8 vs. 26.5 F1), suggesting that the task is closer to traditional captioning since descriptions summarize videos with fewer significant changes compared to comics, where progression between frames is more explicit.

Robotics. In robotics (Robo), IMAGECHAIN (27.1 F1) shows a substantial improvement over MLLM (15.2 F1) and MLLM-FT (14.4 F1), highlighting that explicitly modeling image sequences improves reasoning in multi-step environments, even in zero-shot out-of-domain settings. Visual-Context (27.8 F1) achieves a similar performance,



MLLM-FT

In the image, a white bear is standing on the right side while holding a basketball in his hands and a deer is standing on the left side and look at the basketball.

IMAGECHAIN

In the image, there is a white bear on the right side wearing a red lower and holding a ball in its hands while a deer on the left side is moving its head. The white bear is standing and holding a ball in its hands and the deer is moving its head. The white bear is throwing the ball into the basketball hoop while a giraffe is standing and looking at the basketball hoop. The white bear is walking towards the basketball hoop and putting the ball into the hoop.

Figure 6: Comparison of *next-scene descriptions*. MLLM-FT (standard fine-tuning) describes static observations, while IMAGECHAIN captures sequential actions. Behavioral cues, i.e., key verbs, are highlighted.

suggesting that leveraging prior frames without explicit text descriptions can be effective in this setting.

7 Conclusions

In this work, we introduced IMAGECHAIN, a framework designed to enhance MLLMs with explicit sequential reasoning capabilities, addressing a key limitation in existing MLLMs. Our results demonstrate substantial improvements over baseline models, with strong performance gains in both indomain and zero-shot out-of-domain settings. Our findings highlight the importance of instruction-tuning within a multimodal, multi-turn conversation framework, suggesting promising directions for future work in refining temporal reasoning, scaling to more complex real-world scenarios and applications such as video understanding and robotics.

Limitations

While IMAGECHAIN enhances sequential reasoning by structuring image sequences as multi-turn conversations, it has some limitations. We test our method on LLaVA-NeXT and average the feature vectors over all frames to compute the scenelevel visual representation, a simple yet effective approach. While future work can investigate performance in other models and can explore more advanced methods for combining feature vectors, this experimental setup is sufficient for evaluating our method. Scalability remains a challenge for longer sequences, as maintaining coherence across many turns may require more sophisticated techniques, which can be explored in future work. That said, our framework already models dependencies more effectively than standard MLLMs, making it a strong foundation for further improvements.

Ethics Statement

This work uses publicly available licensed (CC BY 4.0) datasets consistent with their intended use (research) to ensure transparency and reproducibility. While IMAGECHAIN enhances sequential reasoning, it may inherit biases from pre-trained models and datasets. Our framework is designed for research and development purposes, and we encourage responsible use, particularly in applications involving decision-making in sensitive domains such as healthcare and robotics. We acknowledge the use of Microsoft Copilot (https://copilot.microsoft.com/) during the development of the coding experiments.

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A Evaluation Prompt

```
<|start_header_id|>system<|end_header_id|>
You are a pattern-following assistant that can only answer with "Yes" or "No". Your goal is to determine whether a predicted caption
conveys a similar enough meaning to the ground truth caption provided.<|eot_id|><|start_header_id|>user<|end_header_id|>
### Instruction:
Determine if the predicted caption conveys a similar meaning to the ground truth caption.
### Ground truth caption:
A man is riding a bicycle through a park.
### Predicted caption
A person is cycling along a path in a park.
### Does the predicted caption convey a similar meaning to the ground truth caption (Yes or No)?<|eot_id|>
<|start_header_id|>assistant<|end_header_id|>
Yes<|eot_id|><|start_header_id|>user<|end_header_id|>
Good job! Indeed, the predicted caption conveys a similar meaning to the ground truth. Both describe a person riding a bicycle in a
park, even though different words are used. The core meaning is preserved.
Determine if the predicted caption conveys a similar meaning to the ground truth caption.
### Ground truth caption:
A woman is sitting on a wooden bench in the park, reading a paperback novel under the shade of a tree.
### Predicted caption:
A woman relaxes in a shaded area of the park, sitting on a bench while enjoying a book.
### Does the predicted caption convey a similar meaning to the ground truth caption (Yes or No)?<|eot_id|>
<|start_header_id|>assistant<|end_header_id|>
Yes<|eot_id|><|start_header_id|> user<|end_header_id|>
Great! Although the wording differs, the predicted caption captures the essence of the ground truth. Both describe a woman sitting on a
bench in a shaded park area, reading a book. While the predicted caption simplifies certain details, such as omitting the specific mention
of the "paperback novel" and "under the shade of a tree," it still conveys the same overall scene and activity, making the meaning similar.
Let's do one more. Remember to answer with one word either "Yes" or "No".
Determine if the predicted caption conveys a similar meaning to the ground truth caption.
### Ground truth caption:
### Predicted caption:
### Does the predicted caption convey a similar meaning to the ground truth caption (Yes or No)?: <|eot_id|> <|start_header_id|>
assistant <|end_header_id|>
```

Figure 7: Evaluation prompt used with Llama 3 70B to annotate the predicted descriptions. The prompt structure is adapted towards description prediction from Alpaca-Eval. The positions are indicated by placeholders [...], where the ground truth and predictions to be annotated are inserted.