MEEL: Multi-Modal Event Evolution Learning

Anonymous ACL submission

Abstract

Multi-modal Event Reasoning (MMER) endeavors to endow machines with the ability to comprehend intricate event relations across diverse data modalities. MMER underlies a wide broad of applications. Despite extensive instruction fine-tuning, current multi-modal large language models still fall short in such ability. The disparity stems from that events exhibit underlying principles governing their evolution and development. Existing training methods are insufficient to capture event evolution mechanisms in various scenarios. In this paper, we introduce Multi-Modal Event Evolution Learning (MEEL) to enable the model to grasp the entire event evolution mechanism yielding advanced MMER ability. Specifically, we commence with the design of event diversification to gather seed events from a rich spectrum of scenarios. Subsequently, we employ ChatGPT to generate evolving graphs for these seed events. We propose the instruction encapsulation process which adapts the evolving graphs into instruction-tuning data, enhancing the model's training. To further improve the evolution process, we implement the guiding discrimination paradigm, in which we design various event negative mining strategies and train the model in precise event classification. Extensive experiments on nine downstream datasets validate the effectiveness of our approach, showcasing state-of-the-art performance in open-source multi-modal LLMs.

1 Introduction

Events are instances or occurrences that are the fundamental semantic units. Events are not independent, and they are usually interconnected by the following relations: causality, temporality, and intention. The goal of Multi-modal event reasoning (MMER) is to comprehend these events and their relations in both visual and textual modalities, and finally pave a path to better understanding the true world. MMER is expected to serve as

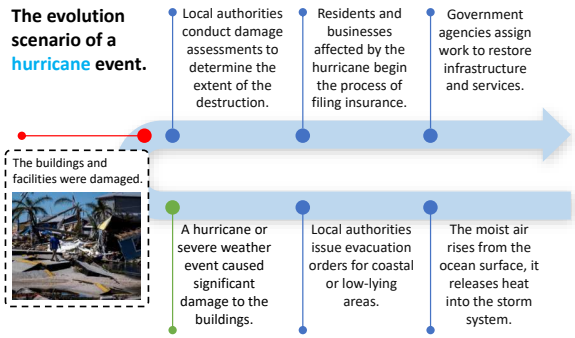


Figure 1: Part of the evolution scenario of a hurricane event. The queried event is in red. MEEL endows the model with the knowledge of all events in the scenario evolution. Current methods only train the model of few clips of event reasoning of the green one.

the underpinning for various multi-modal applications, including visual storytelling (Huang et al., 2016), visual event prediction (Huang et al., 2021), event-related VQA (Park et al., 2020), and MM knowledge graph construction (Ma et al., 2022). Such intricate tasks require an understanding of the event evolution mechanism across diverse data modalities.

With the deepening of research on multi-modal instruction tuning, MM large language models have been able to handle various Multi-Modal tasks effectively (Liu et al., 2023; Zhu et al., 2023; Chen et al., 2023; Dai et al., 2023; Li et al., 2023b). These models master the ability of MM event relational reasoning implicitly during training of diversified sorts of tasks. Among all the task categories, the perception tasks such as referring expression comprehension, referring expression generation, and grounded image captioning (Mao et al., 2016; Kazemzadeh et al., 2014; Peng et al., 2023) enable the model to comprehend the entities of the events in the image and text. The cognitive tasks, namely image caption and VQA (Lin et al., 2014; Goyal et al., 2017), endow the model with the semantic understanding capability of events. However, the models trained by these tasks are unable to per-

ceive event evolution because of the static nature of all modality inputs. Existing visual instruction-tuning methods only consist of questions for few clips of the entire event scenario. As shown in Figure 1, current methods only model the queried events with the green event and ignore the rest of the scenario. They lack a vision of a broad spectrum of other events in the evolving context. Such contextual absence impedes models from learning abundant evolution knowledge resulting in poor performances in MMER.

In order to address this issue, we propose Multi-Modal Event Evolution Learning (MEEL) for endowing the model to understand the event evolution, so as to enhance the ability of MMER to improve the performance of downstream tasks. Specifically, we first design the event scenario diversification to acquire various of events from abundant scenarios. Then we employ ChatGPT to generate the evolving graphs of these seed events as shown in Figure 1. The aim is to use these graphs to train the model to understand the rich knowledge of the evolution of events. To accomplish this goal, we propose the instruction encapsulation process to adapt the evolving graphs into instruction-tuning data to train the model. In this way, the training allows the model to comprehend more event relational knowledge of the scenario leading to better performance of event reasoning. However, it is not enough to let the model learn only the evolving graphs. Without acknowledging what are the incorrect evolving events, the model would rashly forward the process attributed to the hallucination of event reasoning. To mitigate this problem, we perform the guiding discrimination. The model requires to judge the incorrect evolution. We design various negative mining strategies to harvest incorrect events. Then we train the model to classify the right event. We also adapt the guiding discrimination into instruction tuning. After obtaining the data, We finetune the LLaVA (Liu et al., 2023) model after its stage-1 pretaining with LoRA (Hu et al., 2021) to get our model.

To validate the effectiveness of MEEL, we conducted extensive experiments on nine datasets that require MMER. They cover visual storytelling, visual event prediction, and event-related VQA. We achieve state-of-the-art in open-source MM LLMs. The results demonstrate that our method does enhance the MMER ability of the model yielding significant improvements in downstream tasks. We conclude our contributions as:

- We propose the Multi-Modal Event Evolution Learning (MEEL). It aims to train the model to comprehend the intricate event evolution of diversified scenarios. Our method may shed light on other MM event reasoning research.
- We further design the Guiding Discrimination to guide the evolution and mitigate the hallucinations of MMER.
- We conduct extensive experiments on nine downstream datasets to test the effectiveness of our model. We achieve SOTA performance among open-source MM LLMs.

2 Multi-Modal Event Evolution Learning

We strive to enhance a multi-modal large language model's capability in multi-modal event reasoning (MMER) to boost performance on downstream tasks. Our approach, Multi-Modal Event Evolution Learning (MEEL), is introduced and structured as follows: Section 2.1 details the MMER task. In MEEL, we initiate with an event diversification step to generate a diverse mix of seed events (Section 2.2), followed by the construction of event-evolving graphs through event graph evolution (Section 2.3). Our objective is to leverage these event-evolving graphs to inform model training. To this end, we encapsulate these graphs into suitable formats for instruction tuning using instruction encapsulation (Section 2.4). Note that instruction tuning is one of the feasible ways to learn the knowledge of event-evolving graphs. One can also leverage other methods such as in-context learning. Additionally, we incorporate a guiding discrimination training strategy to refine evolution pathways and reduce reasoning errors (Section 2.5). MEEL's comprehensive framework is graphically represented in Figure 2.

2.1 Multi-Modal Event Reasoning

Multi-Modal Event Reasoning (MMER) involves deducing relationships and narratives across different modalities, enhancing comprehension of events that are described by both textual and visual elements. Specifically, events as semantic units can be characterized by text, but their semantics are often more richly conveyed through associated images (Zhang et al., 2021b). The pursuit of MMER is to harness these multi-modal inputs to establish various relationships between events (temporal, causal, intentional, etc.), facilitating sophisticated reasoning processes (Tao et al., 2023b,a; Han et al.,

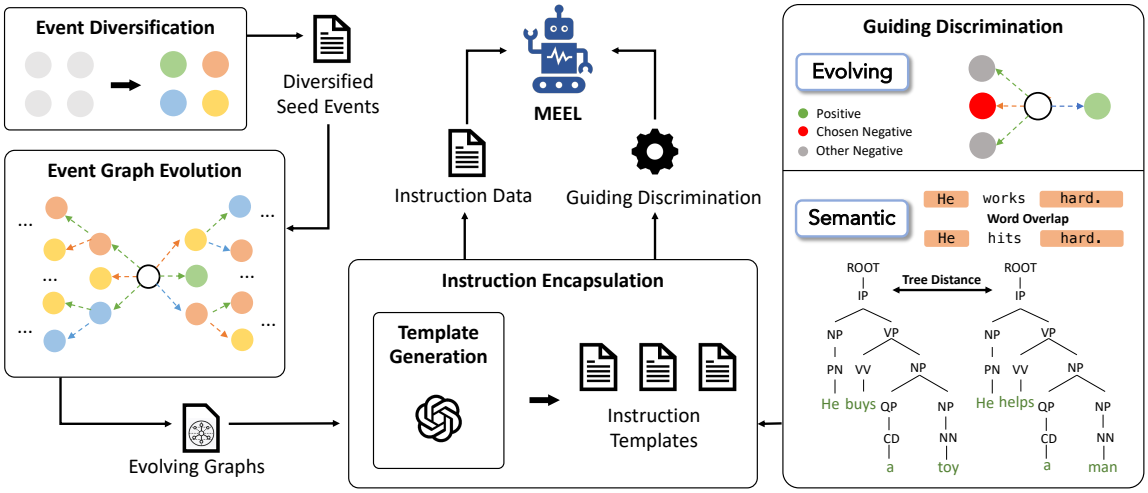


Figure 2: Overview of MEEL. We first implement the Event Diversification to harvest seed events. Then we perform the Event Graph Evolution to obtain the evolving graphs. We adapt the evolving graphs into instruction-tuning data through our Instruction Encapsulation. The Guiding Discrimination aims to improve the evolution learning with our two negative event mining strategies.

2021). This reasoning extends to a spectrum of downstream tasks (Huang et al., 2016; Park et al., 2020; Huang et al., 2021).

We elaborate on the MMER formulation, wherein an event is expressed by a textual sentence $\mathcal{E}$ and represented by an image $\mathcal{I}$. Text provides argument structure, such as subject, verb, and object (Doddington et al., 2004), while images contextualize the event with environmental and situational details (Yang et al., 2023; Zellers et al., 2021). MMER can be modeled as inferring a target event $\mathcal{E}^t$ based on a given relationship $\mathcal{R}$:

$$\mathcal{E}^t = \mathrm{M}\left(\mathcal{E}, \mathcal{I}, \mathcal{R}\right), \quad \mathcal{R} \in \mathbb{S}^{\mathcal{R}} \tag{1}$$

Here, M denotes the reasoning model and $\mathbb{S}^{\mathcal{R}}$ represents the set of possible inter-event relations. Notably, the model allows for the absence of either $\mathcal{E}$ or $\mathcal{I}$ in the reasoning process.

2.2 Event Diversification

Event diversification aims to curate a varied collection of seed events, encompassing multiple types and scenarios for ensuing evolutionary learning. We initiate this process with a corpus of text and image pairs $\{(\mathcal{E}_i, \mathcal{I}_i)\}$, where each pair jointly represents an event. Focusing on event triggers, which are typically verbs that explicitly signify the event's occurrence (Doddington et al., 2004), we employ the Spacy tool[1] to identify the primary verb $\mathcal{V}_{\mathcal{E}_i}$ within each text $\mathcal{E}_i$.

Observing a long-tail distribution in verb frequency, we impose a limit of K events per verb to mitigate the skewness and establish a balanced seed event set, denoted as $\mathbb{S}^{\mathcal{E}} = \{(\mathcal{E}_i, \mathcal{I}_i)\}$. The outcome of this event diversification step is a more comprehensive representation of event types and scenarios, thereby broadening our model's generalization capabilities and strengthening its understanding of varied contexts.

2.3 Event Graph Evolution

For our model to grasp the dynamics of event evolution, we utilize the seed events $\mathbb{S}^{\mathcal{E}}$ to construct event-evolving graphs through our designed event graph evolution methodology. Building on insights from prior work where LLMs like ChatGPT have demonstrated proficiency in generating coherent event narratives (Gunjal and Durrett, 2023; Li et al., 2023e), we apply a breadth-first search (BFS) strategy using the ChatGPT[2] to expand each seed event $(\mathcal{E}, \mathcal{I}) \in \mathbb{S}^{\mathcal{E}}$ both forward and backward in time.

We illustrate the process for the forward evolution, where starting from the seed event $\mathcal{E}$, we consider forward-oriented relations such as $\mathbb{R}^E = \{\texttt{Result}, \texttt{After}, \texttt{HasIntention}\}$[3]. For each iteration of BFS, we invoke the ChatGPT to produce subsequent events in line with sampled relations from $\mathbb{R}^E$, as described in Equation 1. After L iterations, we acquire an event-evolving graph $\mathcal{G}$.

Recognizing the potential bias of relying solely on textual events, which may lack contextual richness, we incorporate visual information. Specifi-

[1] https://spacy.io/

[2] https://openai.com/

[3] Relations are directed from the generated to the queried event, for instance, generating the `Result` for a given event. `HasIntention` implies the head event is intended by subjects in the tail event.

(a) Evolving Prompt

Consider the context that {caption}.Given a mentioned event: {event}, list events that each has a certain relation to the mentioned event. The generated events should be complex and complete which should at least have subject, verb. Leverage richer common sense knowledge to generate events. The generated events and the mentioned event can have different subjects. \nExamples: {examples} \nOutput:

(b) Instruction Generation & Generated Template

Give me 100 instructions. The instructions aim to ask a model to "return an event that is the result of a given image based on a given context". The generated instructions should be as rich as possible in syntax, semantics, and form, covering various task difficulties. Include the context in the generated instructions and mention it as [event]. Don't generate double quotation marks.

Considering the {event}, describe an event that unfolds as a consequence of the depicted image.

(c) Instruction Generation & Generated Template (MC)

Give me 50 instructions that aim to choose the most possible consequence of a given image from given choices based on a given context. The generated instructions should be as rich as possible in syntax, semantics, and form, covering various task difficulties. Include the context in the generated instructions and mention it as [event]. Don't generate double quotation marks.

Draw upon the {event} to interpret the image, then pick the consequence that emerges as the most plausible.

Figure 3: (a) Evolving prompt. The sentence in brown only exists if $\mathcal{E}$ is the seed event, in such case we add the caption of $\mathcal{I}$. (b) Instruction templates generation of `Result` relation and one example of generated template. (c) Multiple-choice Instruction templates generation of `Result` relation and one example of generated template. {caption} is the placeholder for the image caption. {event} and {example} are for the event $\mathcal{E}$ and in-context examples.

cally, while evolving a seed event, we add its image caption to furnish contextual details, promoting more accurate evolution. Intermediate events are evolved using just their text. The prompt template for this evolution process is depicted in Figure 3(a).

Besides, we also consider backward evolution. Our motivation for that is intuitive. We want the model to cognize events in an evolving timeline. We start from an intermediate event, so we need to perform both forward and backward evolution. To do that, we consider evolving relations $\mathbb{R}^E = \{\texttt{Cause}, \texttt{Before}, \texttt{IsIntention}\}$ and remains the other steps the same.

After the evolution, we denote the outputs as the event-evolving graph $\mathcal{G}$s which entails the rich evolution mechanism of the event scenario. We show the process of either direction in Algorithm 1.

2.4 Instruction Encapsulation

To endow the knowledge of in the evolving graphs $\mathcal{G}$ for model training, we turn to multi-modal instruction-tuning, a technique with proven efficiency in adapting models to human-like comprehension (Zhu et al., 2023; Sun et al., 2023; Li et al., 2023a; Liu et al., 2023; Li et al., 2023b; Dai et al., 2023). Our approach involves transforming the components of $\mathcal{G}$, represented as $\mathcal{G} = (\mathbb{V}, \mathbb{W})$ with nodes $\mathbb{V}$ and edges $\mathbb{W}$, into instruction-tuning data.

Algorithm 1: Event Graph Evolution algorithm.

Input : Seed event $\mathcal{E}$ and the caption $\mathcal{C}$, evolving relations $\mathbb{R}^E$, evolving steps L.
Output : Event-evolving graph $\mathbb{G}$.

$\mathbb{G}$.AddNode($\mathcal{E}$), $\tilde{\mathbb{E}} = [\mathcal{E}]$
for $i \leftarrow 1$ **to** L **do**
  $\mathbb{N} = [\,]$
  for $\mathcal{E}_j$ ***in*** $\tilde{\mathbb{E}}$ **do**
    if $i == 1$ **then**
      $\{(\mathcal{E}_k, \mathcal{R}_k)\} =$ Evolve($\mathcal{E}_j, \mathcal{C}$, SampleRel($\mathbb{R}^E, 2$))
    else
      $\{(\mathcal{E}_k, \mathcal{R}_k)\} =$ Evolve($\mathcal{E}_j$, SampleRel($\mathbb{R}^E, 2$))
    end if
    for $\mathcal{E}_k, \mathcal{R}_k$ ***in*** SampleEvent($\{(\mathcal{E}_k, \mathcal{R}_k)\}, 2$) **do**
      $\mathbb{G}$.AddNode($\mathcal{E}_k$)
      $\mathbb{G}$.AddEdge($\mathcal{E}_j, \mathcal{R}_k, \mathcal{E}_k$)
      $\mathbb{N}$.Append($\mathcal{E}_k$)
    end for
  end for
  $\tilde{\mathbb{E}} = \mathbb{N}$
end for
return $\mathbb{G}$

For each node $\mathcal{E}_i \in \mathbb{V}$, we aim to create a datum comprising the seed event $\mathcal{E}^s$, its associated image $\mathcal{I}$, the relation $\mathcal{R}_i$, and the event $\mathcal{E}_i$. However, directly inferring $\mathcal{R}_i$ between nodes $\mathcal{E}^s$ and $\mathcal{E}_i$ is not straightforward if they are non-adjacent. We address this by introducing induction rules that leverage the properties of inter-event relations, as detailed in Table 1. By applying these rules, we derive the indirect relation $\mathcal{R}_i$.

Then we embed all the data with our instruction-tuning templates to form an instruction tuning dataset. For the templates, to avoid the laborious task of manual template creation, we employ ChatGPT to generate diverse question templates for each relation type. With 100 variations from ChatGPT, the templates aim to prompt reasoning about the tail event based on the provided visual and/or textual events in accordance with Equation 1. Considering the possible absence of textual input, we generate two variations for each of the $|\mathbb{S}^{\mathcal{R}}|$ relations: one with textual input and one without.

For any given data $(\mathcal{E}^s, \mathcal{I}, \mathcal{R}_i, \mathcal{E}_i)$, we randomly determine whether to include textual event infor-

mation. We then match a suitable template to the relation type $\mathcal{R}_i$ and encapsulate all the items into our instruction-tuning dataset. An example of an encapsulated datum is illustrated in Figure 3(b).

2.5 Guiding Discrimination

To ensure accuracy during event graph evolution and guide the model away from generating erroneous events, we introduce a guiding discrimination training paradigm. This mechanism is pivotal in preventing the evolution process from producing hallucinations which is similar to DPO (Rafailov et al., 2023). In this paradigm, we task the model with identifying the correct event amongst a set of carefully selected negative events.

The discrimination training is challenging due to the sourcing of these negative events. For which we formulate two acquisition strategies:

Semantic: To forge semantically similar negative events, we first compile a pool of all events of the generated graphs. For any positive event $\mathcal{E}$, utilizing Spacy for dependency parsing, we compute the tree edit distance and the word overlap rate between $\mathcal{E}$ and each event in this pool[4]. Filtering based on preset thresholds for these metrics, we select the top two events that are syntactically close to $\mathcal{E}$. This method sharpens the model's ability to distinguish between events with closely related linguistic structures.

Evolving: This strategy enhances the model's grasp on the directionality of event evolution. Leveraging the bidirectional nature of our event generation, namely forward and backward directions, we select two negative events from the opposite direction of the positive event's evolution. These negatives are particularly challenging as they maintain shared arguments within the same scenario but differ in their logical sequence. This practice further refines the model's reasoning skills for establishing the correct evolution path.

From the total four negative events generated through these strategies, we randomly select two. These, alongside the correct event, are then encapsulated into a multiple-choice format. We also create diverse multiple-choice question templates for each relation type to vary the instruction prompts. An example of such a prompt and a corresponding template is presented in Figure 3(c). Comprehensive statistics of the dataset are detailed in Table 2.

[4]https://github.com/timtadh/zhang-shasha

RULE	INDUCTION
(After)⋆(Result)+(After)⋆	Result
(After)⋆(HasIntention)+(After)⋆	HasIntention
(After)+	After
(Before)⋆(Cause)+(Before)	Cause
(Before)⋆(IsIntention)+(Before)	IsIntention
(Before)+	Before

Table 1: Relation induction rules. ⋆ denotes there exists zero or more. + means there is at least one.

GRAPH	NODE	TRAINSET	INPUT TOKEN
3600	38.36	7470	104.17

Table 2: Trainset statistics.

2.6 Training

We finetune the backbone by combining the MMER loss $\mathcal{L}^R$ (Eq.1) and the guiding discrimination loss $\mathcal{L}^D$:

$$\begin{aligned} \mathcal{L}^R &= -\sum_{(\mathcal{E},\mathcal{I},\mathcal{R})} \log P(\mathcal{E}^t|\mathcal{E},\mathcal{I},\mathcal{R}), \\ \mathcal{L}^D &= -\sum_{(\mathcal{E},\mathcal{I},\mathcal{R},\mathbb{D})} \log P(\mathcal{E}^t|\mathcal{E},\mathcal{I},\mathcal{R},\mathbb{D}), \\ \mathcal{L} &= \mathcal{L}^R + \mathcal{L}^D \end{aligned} \tag{2}$$

3 Experiments

3.1 Datasets

We incorporate nine relational reasoning test datasets to testify our method covering event-related visual question answering, visual event prediction, and storytelling. In this work, we denote the multiple-choice tasks as CLOSE tasks and tasks without candidates as OPEN. We include VCOPA (Yeo et al., 2018), VisCa (Zhang et al., 2021a), VisualComet (Park et al., 2020), IgSEG (Huang et al., 2021), VIST (Huang et al., 2016). Detailed descriptions are in Appendix A.

We also compute the percentage of data leakage of our trainset to each test set. We regard test data as a leakage if the train set has at least one data that has more than 0.5 cosine similarity to it. We report the percentage in Table 5. There's only a small portion of data leakage.

3.2 Baselines

We compare baselines as LLaVA-Lora (Hu et al., 2021), InstructBLIP (Dai et al., 2023), Otter (Awadalla et al., 2023), MiniGPT-4 (Zhu et al., 2023), MiniGPT-4-v2 (Chen et al., 2023). We show more details in Appendix B.

♣	VCOPA-C	VisCa-O	VC-C	VCOPA-O	VisCa-O	VC-O
	VQA					
InstructBLIP (Dai et al., 2023)	63.33	64.78	51.25	7.57 / 2.31 / 9.32	7.56 / 1.01 / 14.87	12.30 / **4.84** / 13.72
Otter (Li et al., 2023b)	57.27	55.97	45.10	11.78 / 1.35 / 17.12	10.29 / 0.51 / 10.51	7.96 / 3.18 / 9.13
LLaVA-Lora (Liu et al., 2023)	46.06	45.28	45.60	7.66 / 1.44 / 0.64	7.06 / 0.67 / 5.66	7.57 / 2.31 / 3.32
MiniGPT-4 (Zhu et al., 2023)	56.67	47.80	51.40	9.78 / 2.44 / 7.05	7.87 / 1.55 / 10.30	6.92 / 1.78 / 0.42
MiniGPT-4-v2 (Chen et al., 2023)	49.70	52.83	54.60	8.90 / 2.13 / 2.09	8.89 / 1.21 / 8.55	7.54 / 3.03 / 5.06
MEEL (Ours)	**66.06**	**72.33**	**68.10**	**19.18 / 2.92 / 26.02**	**19.16 / 3.40 / 29.58**	**16.28** / 3.99 / **22.93**

Table 3: Main results of VQA tasks. The bold number represents the highest score.

♣	IgSEG-C	IgSEG-O	VIST
	PREDICTION		STORYTELLING
InstructBLIP	55.10	8.13/**2.63**/15.91	6.71/1.22/11.31
Otter	53.20	7.57/1.35/4.34	7.63/1.20/10.51
LLaVA-Lora	46.40	9.03/1.50/4.46	9.09/**3.03**/5.53
MiniGPT-4	49.90	8.72/1.54/3.24	8.66/1.67/9.64
MiniGPT-4-v2	51.30	8.69/1.45/3.73	8.95/1.68/10.44
MEEL (Ours)	**66.50**	**14.00**/1.41/**19.41**	**14.38**/1.44/**25.60**

Table 4: Main results of visual event prediction and storytelling. The bold numbers represent the best score.

VCOPA-C/O	VISCA-C/O	VC-C/O	IGSEG-C/O	VIST
5.75/3.63	3.77/2.48	3.85/3.85	3.57/4.36	5.78

Table 5: Trainset leakage percentages.

♣	VQA	PRED	STORY	OPEN	CLOSE	ALL
InstructBLIP	33.01	35.50	11.31	12.53	54.11	25.16
Otter	28.40	28.77	10.51	9.66	49.06	21.64
LLaVA-Lora	23.92	25.43	5.53	4.64	45.85	17.17
MiniGPT-4-v2	26.49	26.57	9.64	6.44	51.30	20.08
MiniGPT-4	28.86	27.51	10.44	7.84	53.11	21.60
MEEL (Ours)	**45.53**	**37.95**	**25.60**	**23.06**	**67.64**	**36.61**

Table 6: Various kinds of average results. The bold numbers represent the best score.

♣	VCOPA-O	VisCa-O	VC-O	IGSEG-O	VIST
MEEL w.o. D	19.63	21.78	21.79	18.83	24.67
MEEL	26.02	29.58	22.93	19.41	25.60

Table 7: Ablation study. MEEL w.o. D is our method without guiding discrimination.

3.3 Implementation Settings

We use InstructBLIP (Dai et al., 2023) to generate the image captions for event graph evolution. We sample two evolving events for each event in the BFS. We set the evolution steps as 3. We finally constructed 15,000 instruction-tuning data.

For our model, we use LLaVA-v1.3 after the first pre-training stage as our backbone (Liu et al., 2023) and train with Lora (Hu et al., 2021), making it comparable to the LLaVA-Lora-v1.3-7B baseline. We use deepspeed[5], zero-2 without CPU offloading. We set the batch size to 16 on 4×V100 GPUs.

In pilot experiments, we conducted tests with multiple input prompts for each model in order to identify the most effective prompts for evaluation. Despite variations in prompts, we observed only minimal fluctuations in the results. To ensure consistency and mitigate the other influences, we maintained uniformity by using the same prompt for all models performing a specific task. Detailed prompts can be located in the Appendix. For the multiple-choice tasks, we transformed them into multiple-choice questions and instructed the model to respond with the corresponding label of choice. For CLOSE tasks, we design an answer decoding strategy and show in Appendix. We find this strategy can handle almost all situations.

[5]https://www.deepspeed.ai/

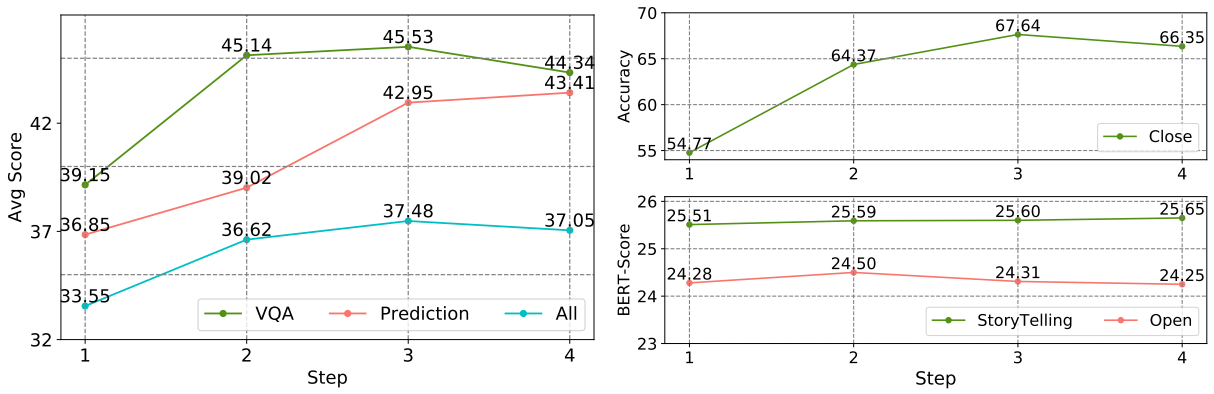
3.4 Evaluation Metrics

For multiple-choice tasks, we employ accuracy as the metric. For OPEN tasks we utilize BLEU-1/2 (Papineni et al., 2002) and BERT-SCORE (Zhang et al., 2019) as measures.

3.5 Main Results

We test our model on 9 downstream tasks. We show the VQA results in Table 3, visual event prediction and visual storytelling in Table 4. We calculate the various kinds of average scores in Table 6.

MEEL can effectively enhance performances of VQA. MEEL achieves the highest scores on three CLOSE VQA, namely VCOPA-C, VisCa-C, and VC-C in Tabel 3. The results indicate MEEL can distinguish the right events since the improvements from event graph evolution with guiding discrimination. For the three OPEN VQA datasets, among all metrics, BERT-SCORE can mostly evaluate the answering quality. We find MEEL outperforms all other baselines to a large extent. These results demonstrate the effectiveness of our method on OPEN VQA. We also notice the BLEU-1/2 of MEEL is higher than almost all models. Since



(a) Average scores on VQA, PREDICTION, and the average of all results.

(b) Average scores on STORYTELLING, all CLOSE tasks, and all OPEN tasks.

Figure 4: Analysis of steps of event graph evolution.

BLEU-1/2 measures lexical similarity, MEEL can generate more well-formed events as the ground truth. In all, our method improves the MMER.

MEEL outperforms baselines in visual event prediction. MEEL performs the best among all baselines in Table 4. The results demonstrate our training method enables the model to capture correct temporal relations leading to more precise prediction for future. Compared to VQA tasks, We find all models perform worse in visual event prediction, indicating it needs more knowledge and reasoning ability to complete this task. In OPEN visual prediction, MEEL also achieves the highest scores in BERT-SCORE. This shows our model can forecast semantic similar events. However, we find MEEL performs slightly lower in BLEU-2 on IgSEG-O. Since BLEU calculates the 2-gram lexical similarity, this may indicate MEEL can predict more diversified events with correct semantics rather than words merely in the context.

MEEL can generate advanced story. In Table 4, we find MEEL can excel all baselines in VIST. The results show MEEL can tell better stories by capturing more scenario knowledge and comprehending the inter-event relations. The event graph evolution affects the training of the model to acknowledge enriched event information rather than merely shallow step reasoning.

In all, MEEL can significantly improve the performance of the downstream tasks attributed to boosted capabilities of MMER. In Table 6, MEEL excels all baselines on the average score of all datasets demonstrating the effectiveness of our method. Our event graph evolution process stimulates the contextual understanding of events. The guiding discrimination further mitigates the hallucinations of event reasoning yielding better performances.

Among all relation types, the improvements of VQA and STORYTELLING are larger than PREDICTION. It indicates our method benefits more for these tasks. PREDICTION is the hardest to learn attributed to its demand for pertaining for more abundant knowledge of events.

3.6 Analysis

Evolution steps. We conduct experiments on different evolution steps to verify the effectiveness of event graph evolution. We tested steps 1-4 respectively and calculated various average scores. We show the results in Figure 4.

As the average of all results, the performance of MEEL increases from steps 1 to 3 in Figure 4 (a). This is consistent with our motivation that the event graph evolution enables the model to learn the rich knowledge of event evolution. Then the model can complete MMER better.

We find the performances drop when the step is too large, namely larger than four. This may be attributed to the semantic drift of the event graph evolution. ChatGPT would generate less relevant content compared to the seed event if it evolves further. We find that the drop is most obvious in VQA, which may be probably due to VQA being the most strict relation among all event interrelations.

We find MEEL can achieve a high score for STORYTELLING when the evolution step is only one in Table 4 (b). MEEL is 25.51 BERT-Score while InstructBLIP is 11.31. As the number of steps increases, MEEL maintains a high score. This indicates that MEEL complete the STORYTELLING even on few evolution steps.

Effect of guiding discrimination. We ablate guiding discrimination and show the results in Table 7. We find that all performances drop if MEEL trains

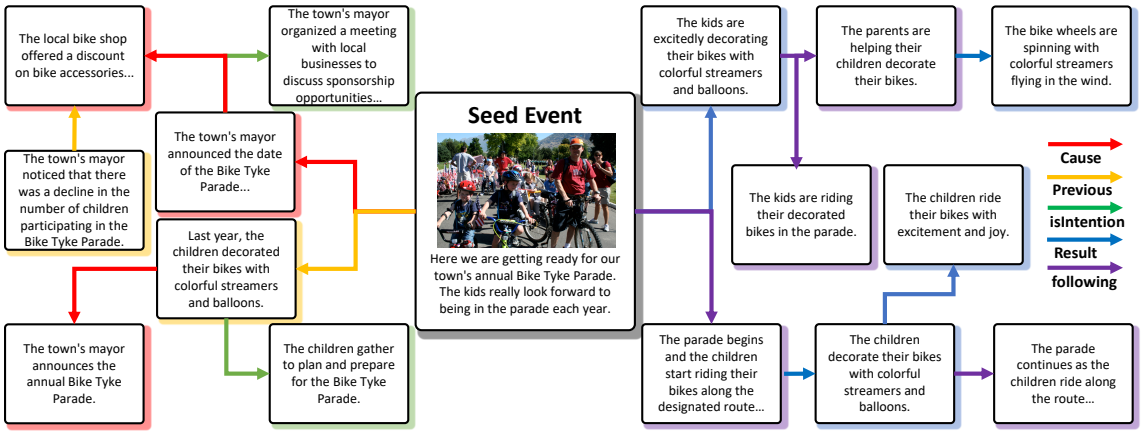


Figure 5: An example of an event-evolving graph. The event pointed to by the head cut is a tail event generated that satisfies the color relationship of the head cut.

without guiding discrimination. It indicates guiding discrimination can guide the evolution and mitigate the hallucinations.

Examples of event graph evolution. We showcase two examples of event graph evolution in Figure 5. We find our evolving graphs can sufficiently contain information and knowledge of event scenarios. With the aid of event-evolving graphs, MEEL learns more abundant event knowledge and relation inter-connections.

4 Relation Works

Multi-Modal Event Relational Reasoning As one of the relation types, causality reasoning is crucial for exploring the cause and effect of events (Yeo et al., 2018; Zhang et al., 2021a; Chadha and Jain, 2021; Ignat et al., 2021). Apart from causality, event temporal reasoning forms a basic ability (Zellers et al., 2019; Park et al., 2020; Zellers et al., 2021). Event intentional reasoning uncovers the intentions of the subjects of the events (Park et al., 2020; Li et al., 2023c). Besides, there exists research on other relation types as well (Kim et al., 2022; Hessel et al., 2022). Multi-modal event relational reasoning constitutes a foundational capability for a range of downstream tasks in the realm of multi-modal reasoning. Our research endeavors to further enhance this crucial skill.

Multi-Modal Instruction tuning With the significant success of instruction tuning (Ouyang et al., 2022), current research has extended its capability to multi-modality. MM instruction tuning trains the model the follow instructions for questions about the images. Compared to textual instruction tuning, harvesting MM data with instructions is tougher. Zhu et al. (2023) trains MiniGPT-4 by further aligning pretrained EVA-CLIP (Fang et al., 2023) and Vicuna (Chiang et al., 2023). Liu et al. (2023) generate visual instruction data by requiring ChatGPT/GPT-4 with the given image and its caption. Dai et al. (2023) adapt human-labeled dataset into instruction data with pre-made templates. Li et al. (2023a) construct in-context learning data with instructions and use this dataset to train an MM LLM. These methods merely model shallow event evolving situations leading to poor ability of MM event relational reasoning.

Script Induction Script induction is to induce or generate chains or graphs of events representing the evolving mechanism. Du et al. (2022) induces 11 scripts of newsworthy scenarios from documents. Gunjal and Durrett (2023) attempt to generate event chains by querying large language models. Zhang et al. (2023) constructs scripts by designing interactions between humans and LLM. Li et al. (2023e) create event graphs in a pipeline operation with generation, ordering, and verification. In our work, we are the first to utilize the ability of script induction from ChatGPT to construct our MM event-oriented instruction-tuning data. We expect our work may shed light on other event-oriented approaches.

5 Conclusion

We propose the Multi-Modal Event Evolution Learning for MMER. We design the event graph evolution process based on the diversified seed events. We then encapsulate the evolving graphs into instruction-tuning data. We introduce the guiding discrimination training paradigm to further improve the learning of evolution. We conduct experiments on three downstream tasks in nine datasets. Results show the effectiveness of MEEL and it achieves SOTA among open-source visual instruction-tuning baselines.

Limitations

Our method is limited to MMER of a single image. However, a more complex MMER may contain several images to express a scenario. We leave the construction of benchmarks and methods of this complex MMER to future work.

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Appendix

A Datasets

We incorporate nine relational reasoning test datasets to testify our method covering event-related visual question answering, visual event prediction, and storytelling. In this work, we denote the multiple-choice tasks as CLOSE tasks and tasks without candidates as OPEN.

`VCOPA` This is the task of commonsense VQA (Yeo et al., 2018). Given an image $\mathcal{I}$ and two candidate options, the task is to select a more plausible cause or effect option. We also transform this dataset into an open reasoning task in which we don't provide the candidates and require the model to generate the answer. We denote the original multiple-choice task as `VCOPA-C` and the transformed task as `VCOPA-O`.

`VisCa` This is a dataset of learning contextual causality from the visual and textual signals (Zhang et al., 2021a). The original task is formulated as that given two images as the context and two textual sentence descriptions, models need to determine if the former sentence causes the latter one. We transform it into our VQA task. We keep the image and first sentence and regard the second sentence as the label to generate. We retrieve one negative sentence by the ground truth and form it as a multiple-choice task. We also adapt the multiple-choice task into an open reasoning similar to `VCOPA-O`. We denote these two tasks as `VisCa-C` and `VisCa-O`.

`VisualComet` This is an open commonsense VQA task which is to answer situations before or after (Park et al., 2020). We also retrieve a negative answer to formulate it into a multiple-choice task. We denote these two tasks as `VC-O` and `VC-C`.

`IgSEG` This dataset aims to predict future events based on what has happened (Huang et al., 2021). Specifically, given a sequence sentences in sequential order and the image of what will happen next, the models need to generate a sentence for this image. In addition, we also retrieve one negative event and form it as a multiple-choice task. We denote these two tasks as `IgSEG-O` and `IgSEG-C`.

`VIST` It's the storytelling task which is to generate next story given the previous story in sentences and an image (Huang et al., 2016).

B Baselines

LLaVA-Lora This is a MM LLM on visual instruction-tuning. It's based on the visual encoder ViT-L/14-336px (Radford et al., 2021) and the textual chat LLM vicuna-v1.3-7b (Chiang et al., 2023). In the first pre-train stage, it is trained with image-text pairs. In the second stage, it is fine-tuned by LLM-generated instruction-tuning data with LoRA (Hu et al., 2021).

InstructBLIP It uses BLIP-2 (Li et al., 2023d) framework as its foundation, InstructBLIP strategically restructures 26 pre-trained public datasets, including image captioning and VQA, into a format conducive to instruction tuning (Dai et al., 2023).

Otter This model combines multi-modal in-context learning with multi-modal instruction tuning, building upon the foundation of Open-Flamingo (Awadalla et al., 2023). This involves updating the perceiver module and relevant components of the LLM throughout the training process. The instructional data is sourced from reputable datasets including VQAv2 (Antol et al., 2015), GQA (Hudson and Manning, 2019), LLaVA, as well as a proprietary video dataset not available to the public.

MiniGPT-4 This model conducts visual instruction tuning on the pre-trained BLIP-2 (Li et al., 2023d), specifically focusing on updating the linear layer (Zhu et al., 2023). The instructions primarily draw from the domain of image captioning tasks.

MiniGPT-4-v2 This model performs as a unified interface to complete various tasks such as VQA, visual grounding, and image caption (Chen et al., 2023). Different from MiniGPT-4, it adds task identifiers into the prompt to guide the task completion. The backbone of MiniGPT-4-v2 is LLama-2 (Touvron et al., 2023).

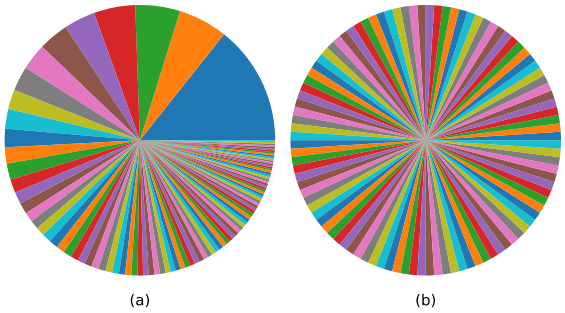

Figure 6: Each part of the pie chart is a proportion of a verb. We present the 100 most frequent verbs with and without event diversification. (a) w.o. event diversification. (b) w.t. event diversification.

C Event diversification

We calculate the event verb distribution. We show two statistics of verb distributions with or without

event diversification. The results are in Figure 6. We find the distribution is significantly diversified after the event diversification process. It enables MEELto be trained in various scenarios and domains.

D Decoding Protocol

We show our decoding protocol for extracting answers of CLOSE tasks as in Algorithm 2:

Algorithm 2: CLOSE tasks decoding algorithm.

Input : *Prediction*
Output : *Answer*

pattern = "the(?: correct)? (?:option|answer) should be[\s:]+([ABCDEFGH])"
if *Output starts with an alphabetical number* **then**
  Set *Answer* as the alphabetical number
else if *re.match(pattern, Output)* **then**
  Extract the *Answer* follow the *pattern* from *Prediction*.
else
  Answer=$\underset{c \in \mathbb{D}}{argmax}(\text{WordOverlap}(c, \textit{Prediction})$
return *Answer*

E Inference Prompts

We show inference prompts of all test set in Figure 7. We test various prompts in our pilot experiments and choose the prompts shown in Figure 7 which perform the best among others. We use the same prompts for all models.

VisualComet

temporal-open

Before:
From the picture, what happened before "{event}"?

After:
Form the picture, what happened after "{event}"?

temporal-close

Before:
Answer the question by returning A or B.

Question: From the picture, what happened before "{event}"?
Choices: {cs}
The answer is

After:
Answer the question by returning A or B.

Question: From the picture, what happened after "{event}"?
Choices: {cs}
The answer is

intentional-open

Input:
In the picture, {event}, what is the intent?

intentional-close

Input:
Answer the question by returning one of the choice from given Choices.

Question: What is the intent of the subject in "{event}"?
Choices: {cs}
The answer is

IgSEG

open

Before:
From the picture, what happened before "{event}"?

After:
Form the picture, what happened after "{event}"?

close

Before:
Answer the question by returning A or B.

Question: From the picture, what happened before "{event}"?
Choices: {cs}
The answer is

After:
Answer the question by returning A or B.

Question: From the picture, what happened after "{event}"?
Choices: {cs}
The answer is

VIST

open

Before:
From the picture, what happened before "{event}"?

After:
Form the picture, what happened after "{event}"?

VCOPA

open

Cause:
What caused "{event}"?

Effect:
What is the result of "{event}"?

close

Cause:
Answer the question by returning A or B.

Question: What is causes "{event}"?
Choices: {cs}
The answer is

Effect:
Answer the question by returning A or B.

Question: What is the result of "{event}"?
Choices: {cs}
The answer is

VisCa

open

Cause:
What caused "{event}"?

Effect:
What is the result of "{event}"?

close

Cause:
Answer the question by returning A or B.

Question: What is causes "{event}"?
Choices: {cs}
The answer is

Effect:
Answer the question by returning A or B.

Question: What is the result of "{event}"?
Choices: {cs}
The answer is

Figure 7: Inference prompts of all test set.