OpenLEAF: Benchmarking Open-Domain Interleaved Image-Text Generation

Anonymous ACL submission



(a) OpenLeaf's evaluation and justification on an interleaved sequence by our baseline method. (b) Performance comparison between baseline methods.

Figure 1: *OpenLEAF* can evaluate the quality of the interleaved content and give clear justifications like human (a), which is a robust tool to compare interleaved generative models' performance on diverse aspects (b). *SP* and *LP* denote short and long text-to-image prompts, respectively.

Abstract

We introduce OpenLEAF, a benchmark designed for the open-domain interleaved imagetext generation task. This task aims to generate arbitrarily-interleaved multimodal content from input queries. It goes beyond single-modality image or text generation, thereby enabling various novel applications by creating content such as visual storybooks and how-to instructions. Despite the importance of the task, there lacks established benchmark due to the challenges in defining evaluation scenarios and formulating effective metrics. In this study, we collect a dataset covering queries with various input-output formats and 10 different application scenarios. We also propose an evaluation pipeline named "detection-summarizationscoring," which breaks down the evaluation into multiple reasoning steps. This pipeline leverages large multimodal models (LMMs) to thoroughly evaluate ten aspects of the generated content, which lead to the final rating. With experiments on a proposed agent system, we demonstrate that our evaluation method aligns closely with human judgments, offering a robust benchmark for assessing interleaved image-text generation.

1 Introduction

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Open-domain interleaved image-text generation, aimed at generating multimodal content that follows user queries, has been desired for long in content generation. As shown in Fig. 1, the task is to generate an interleaved sequence of text descriptions and illustrative images that are coherent and correspond to user's text and image queries. The "open-domain" aspect indicates its adaptability to generate content freely across multiple domains, enabling the creation of complex content from visual instructions and illustrated stories to webpages. Such multimodal generation could redefine how we create and consume content in in various fields, such as education, marketing, etc.

Despite the significance of the task, there lacks standardized evaluation benchmarks, mainly due to the challenges in creating a comprehensive evaluation set and formulating effective metrics. In this study, we introduce *OpenLEAF*, a comprehensive benchmark that includes an evaluation dataset, a novel evaluation pipeline, and a baseline generation system, to standardize the task evaluation.

OpenLEAF Data and Topology. One primary challenge of *OpenLEAF* is establishing standard evaluation queries and scenarios as a benchmark. With a focus on model generalizability and robustness (Zhang et al., 2021; Torralba and Efros, 2011), we categorize classes based on input formats and application domains and collect real user queries. This dataset includes 500 text-based

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Figure 2: Visualization of selected topics in *Open-LEAF*. We show selected images in the generated interleaved content to visualize query scenarios in our *OpenLEAF* dataset. *OpenLEAF* covers diverse inputoutput formats and application scenarios. Blue image captions indicate the story generation task, while the red captions denote visual how-to instructions.

prompts across 10 different topics. Examples of these topics, as depicted in Fig. 2, include instructional cooking recipes, storybooks about specific characters, arts and crafts, etc. Besides, we collect 100 queries with reference texts, and 60 queries with image-text sequences as the reference to comprehensively test a model's capabilities.

OpenLEAF Evaluation. Beyond data topology, another challenge is formulating an effective automated evaluation method suitable for interleaved image-text content. This method should comprehensively evaluate different aspects of the generation content. Existing evaluation methods, such as Visual-Language (VL) models (Radford et al., 2021; Li et al., 2022, 2023c; Chen et al., 2023) and specialized tools (Li et al., 2019; Maharana et al., 2021), fall short in evaluating detailed aspects like identity and style. Tab. 1 summarizes the capability of existing evaluation approaches, where none of them can be directly applied in *OpenLEAF*.

Inspired by the capabilities of LMMs (OpenAI, 2023b,c; Google, 2023; Microsoft, 2023; Yang et al., 2023), we use LMMs to evaluate open-domain content from various aspects of interest. We present a GPT-4V-based "detectionsummarization-scoring" pipeline that comprehensively evaluates 10 aspects of the generated contents, i.e., *image fidelity, aesthetics, image-text coherence, identity consistency, style consistency, and the multi-modal input-output consistency in terms of the text, identity, visual style, subject's attribute, and overall image following ability.* For each aspect, the pipeline first *detects* key elements for that aspect, *summarizes* its findings, and *scores* the generated content based on the summarization.

Baselines. Ensuring semantic and visual style alignments across image-image, image-text, and text-text combinations poses a significant challenge

Evaluation Approach	Text Following	Image-Text Alignment	Image Attribution/Style Alignment
Chiang and Lee (2023)	 Image: A second s	×	×
GPTEval (Liu et al., 2023c)	1	×	×
GPTScore (Fu et al., 2023)	 Image: A second s	×	×
CLIPscore (Radford et al., 2021)	×	1	×
BLIP (Li et al., 2023c)	×	1	×
VisualGPTScore (Lin et al., 2023b)	×	1	×
Black et al. (2023)	×	1	×
Liu et al. (2023b)	×	1	×
LLMScore (Lu et al., 2023)	×	1	×
X-IQE (Chen et al., 2023)	×	1	×
Betti et al. (2023)	×	✓	×
OpenLEAF (Ours)	 Image: A second s	1	1

Table 1: **Capability comparison of open-domain evaluation methods in terms of the content alignment.** Thanks to the ability of pre-trained LMMs such as GPT-4V in capturing fine image details as well as a carefully designed prompting pipeline, *OpenLEAF* can evaluate complex mixed media alignments, facilitating the evaluation of interleaved content.

in interleaved generation. Naively combining textto-image (T2I) and image-to-text generations fail to generate coherent content. We present an agent system as the baseline for OpenLEAF, leveraging LMM and T2I models. Specifically, we use GPT-4V to generate texts and T2I prompts. To enhance the image consistency of generated sequences, global entity contexts and unified style descriptions are added to all T2I prompts. Then T2I models like DALL-E 3 (OpenAI, 2023d) and Stable Diffusion XL (SDXL) (Podell et al., 2023) are adopted to convert T2I prompts into images and form the interleaved sequence. We validate our proposed evaluation pipeline on this agent system through extensive analyses. Results show a strong correlation with human ratings of the generated interleaved content, indicating the effectiveness of the OpenLEAF benchmark.

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Our contributions are summarized as follows.

- We build dataset of 660 samples for evaluating open-domain interleaved image-text generation, covering diverse formats and scenarios.
- We propose an LMM-based evaluation pipeline, named "detection-summarization-scoring," which evaluates generated content across 10 aspects with detailed justifications and ratings.
- We present a baseline agent system, and evaluate its generation with both LMM and humans. The high correlation with human ratings show that our pipeline is effective in evaluating multimodal contents, serving as a proxy for human ratings.

Input Type	Торіс	# Problem
	Cooking and Recipes	50
	Travel and Places	50
	Fitness and Well-being	50
	Home Improvement and DIY	50
User Query	Arts and Crafts	50
Only	Gardening and Plant Care	50
	Story Requests about Specific Characters	50
	Story Requests about General Subjects	50
	Myths, Legends, and Historical Tales	50
	Adventure and Exploration	50
User Query	Animal Stories	50
+ Text Context	Brand Introductions	50
Input Type	Input Image Function	# Problem
	An image indicating the identity	20
User Query	Dual images indicating identities	10
+ Text Context	An image indicating the image style	10
+ Image Context	An image indicating the attribute	10
	An image indicating the first image	10
Overall		660

Table 2: A summary to our collected benchmark dataset. The dataset covers diverse topics while setting challenges in satisfying various requirements related to input images.

2 Related Work

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Interleaved Image-Text Generation. Current interleaved image-text generation methods, including StoryGen (Liu et al., 2023a), AR-LDM (Pan et al., 2022), and StoryDALL-E (Maharana et al., 2022), primarily use fine-tuned latent diffusion models (LDMs) (Rombach et al., 2022) or text-to-image transformers. These approaches, however, are limited in open-domain generation due to fine-tuning on specific datasets. The challenge of evaluating open-domain interleaved content is still unresolved. Recent multi-modal LLMs like GILL (Koh et al., 2023), Emu (Sun et al., 2023), and Dream-LLM (Dong et al., 2023) show promise in opendomain image-text tasks but are not specifically designed for interleaved generation and evaluation, leaving a gap in this area.

Foundation Models for Open-Domain Evalua-144 tion. Designing benchmarks (Trabucco et al., 2022; 145 Zhu et al., 2023; Huang et al., 2023; Li et al., 2023a) 146 and evaluating open-domain content has drawn in-147 creasing attention. In natural language process-148 ing, studies have shown the potential of prompt-149 ing LLMs like GPT for open-ended text evalua-150 tion (Chiang and Lee, 2023; Liu et al., 2023c; Fu et al., 2023). For visual-language content, methods 153 such as CLIPscore (Radford et al., 2021), BLIP (Li et al., 2022, 2023c), VisualGPTScore (Lin et al., 154 2023b), LLaVA-based scoring (Black et al., 2023; 155 Liu et al., 2023b), LLMScore (Lu et al., 2023), X-IQE (Chen et al., 2023), and Betti et al. (2023) can 157

Input Type | Rubric Chain-of-Thought Detection ↔ Summarization ↔ Scoring Image Fidelity Artifacts Per Imag Image Aesthetic Aesthetic Features Per Image Image-Text Coherence Per Image-Text Image-Text Mismatch Per-Image Subjects/Objects Major Subjects/Obje Per Identity Identity Consister Appearance Media Type Style Consistency Per Visual Aspect Tint. Saturati Overall Input-Output Per Identity Identity Appearance Per Input-Ouput Pair Per Visual Aspect Per Input-Ouput Pair nput-Outp tity Consis Commor Identity Media Type Input-Output Sequence Input-Out yle Consis Color Pa Tint, Saturatio Pair Target Attribute Attribute Per Input-Output Pair Appearance Coherency after acing Output Image repla Overall 1 with Input In

Figure 3: An overview of the LMM-based evaluation pipeline. We evaluate the quality of interleaved content on 10 aspects based on a detection-summarization-scoring process.

effectively assess image-text similarity. However, they are limited to single image-text pairs and cannot fully evaluate interleaved content. Our work overcomes these limitations by using LMMs (OpenAI, 2023c) to evaluate open-domain interleaved content, accepting multiple image-text pairs for a more open-ended evaluation. 158

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Multi-Modal Agents. As a baseline for opendomain interleaved generation, the presented agent system is related to multi-modal agent studies (Gupta and Kembhavi, 2023; Surís et al., 2023; Wu et al., 2023; Yang* et al., 2023; Shen et al., 2023; Li et al., 2023b; Lin et al., 2023a), which chain LLMs with multi-modal tools for new tasks. For example, Visual ChatGPT (Wu et al., 2023) shows that allocating various generative models (Rombach et al., 2022; Meng et al., 2021; Zhang and Agrawala, 2023) with ChatGPT (OpenAI, 2023a) can achieve complicated image generation and editing. Differently, our work focuses on a specific challenging task of open-domain interleaved image-text generation.

3 Method

This section details the evaluation dataset collection process, outlines our evaluation pipeline using LMM, and explains how we build the agent system using GPT-4V and T2I models to form opendomain interleaved generation baselines.

3.1 Data Collection

Tab. 2 outlines our evaluation dataset for opendomain interleaved content generation, detailing

problem types, formats, topics, and counts. The 189 dataset is structured into three categories: user 190 queries only, user queries with textual context, and 191 user queries with multi-modal image-text context. 192 In the user query only category, we assess the model's ability to generate varied topics like cook-194 ing recipes and DIY instructions. This includes 50 195 problems per topic, totaling 500 problems across 196 10 topics, created via GPT-4 prompts. The second category, encompassing user queries with textual 198 context, features 100 problems where users add reference texts, such as stories or brand introductions, for integration into visual stories or webpage 201 outputs. Lastly, the category involving user queries 202 with multi-modal image-text context contains 60 203 problems. These problems are designed to assess the model's proficiency in following user-defined specifications, such as maintaining identity and visual style, aligning attributes with the input im-207 age, and generate interleaved content based on the input image. In sum, the OpenLEAF dataset offers a substantial set of 660 problems, providing a robust framework for evaluating performance in open-domain interleaved content generation. 212

3.2 Evaluation Pipeline

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Our evaluation approach, utilizing GPT-4V (OpenAI, 2023c), imitates human judgment in analyzing interleaved content through a three-stage process: detection, summarization, and scoring. In the detection phase, GPT-4V examines the interleaved content to identify key elements relevant to our evaluation criteria. Next, in the summarization stage, it consolidates these findings into a clear summary, setting the stage for scoring. Finally, GPT-4V scores the content using a scale of 0, 5, 10, where 10 represents excellent performance, 0 indicates significant flaws, and 5 reflects satisfactory content with minor issues. This streamlined method ensures a concise yet comprehensive evaluation. In our approach, as illustrated in Fig. 3, we assess the quality of interleaved content across 10 distinct aspects. These aspects are grouped into four categories, each reflecting a different scope of evaluation. The overall evaluation score is the average of scores obtained in each of these aspects.

Single Image. The evaluation of a single image encompasses both its fidelity and aesthetics. Fidelity assessment involves GPT-4V's analysis for artifacts such as blurriness or inconsistency, with scores given for visual fidelity. In aesthetics evalu-238



Figure 4: A baseline interleaved generation method based on prompting LMM and T2I models. We add global context into T2I prompts to encourage the visual consistency of images in the interleaved content.

ation, GPT-4V scores the image based on artistic elements. These two aspects offering a rounded appraisal of an image's technical and artistic merit.

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Image-Text Pair. To evaluate the coherence of image-text pairs, we employ GPT-4V. Initially, both the image and corresponding text are inputted into the model. GPT-4V then detects any incongruities, assigning scores reflecting the number and importance of these discrepancies.

Generated Interleaved Sequence. To evaluate identity and style consistency, GPT-4V first extracts key subjects/objects from text descriptions, summarizes their appearance across images, and scores their visual consistencies across images. For style, it examines four dimensions: media type (realistic, painting, cartoon), color palette (monochromic, polychromic), tint (warm, cold), and saturation (high, low), scoring each image's adherence to these style parameters.

Input-Output Sequence. we evaluate the coherence of input-output multi-modal sequences on text alignment, identity and style consistencies, attribute consistency, and image following performance. Text alignment is assessed by comparing input and output texts through GPT-4V to ensure they match user requests. Identity and style consistencies are evaluated by comparing each inputoutput image pair, similar to output-only sequences. Attribute consistency is determined by extracting target attributes from user inputs and evaluating how well they're reflected in each input-output pair. Image following examines the content coherence when the first output image is replaced with the input image. These evaluations are conducted only for sequences where specific attributes, identities, styles, or starting images are provided by the user.

	Singl	e Image↑	Image-Text Pair↑	Output In	terleaved↑		Input-	Output Interl	eaved↑		
Method	Fidelit.	Acothotico	Coherence	Identity	Style	Text	Entity	Style	Attribute	Image	Average↑
	Fidelity Aesthetics		conerence	Consistency	Consistency	Alignment	Consistency	Consistency	Consistency	Following	
GPT-4V (SP) + SDXL	9.38	8.09	7.07	6.56	8.00	10.0	5.94	7.65	4.63	7.5	7.48
GPT-4V (SP) + DALL-E 3	9.13	8.80	8.07	7.02	8.85	10.0	7.68	8.44	4.75	7.94	8.07
GPT-4V (LP) + DALL-E 3	9.62	9.01	8.62	7.16	8.76	10.0	9.35	8.71	4.06	7.97	8.33

Table 3: **The comparison of baseline results.** *SP* denotes "Short Prompts", where T2I prompts contains at most 77 tokens per the requirement of SDXL. *LP* denotes "Long Prompts", where the word length of T2I prompt is roughly capped by 150. The highest and the second highest figures are highlighted by green and orange backgrounds, respectively. The full score is 10.

3.3 Interleaved Generation Baselines

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We introduce an agent system that combines GPT-4V (OpenAI, 2023c) with text-to-image (T2I) models like DALL-E 3 or SDXL through textual prompts, setting a baseline for the open-domain interleaved generation task. As depicted in Fig. 4, the system initiates with a user query and a multimodal input. A meticulously devised composition strategy crafts an input prompt detailing the desired content, format, contextual examples, and output constraints. These examples enable GPT-4V to grasp the expected content, fostering generation in the example's format and facilitating the automatic result extraction. Following this, GPT-4V processes the prompt and context, generates text descriptions, determines image insertion points, and crafts T2I prompts for image creation.

To ensure consistency in entity depiction and stylistic elements, we enrich the visual prompts with global entity and style contexts. The global entity context is a set of concise descriptions of each key subject's appearance. For the global style context, GPT-4V crafts it by selecting a suitable visual style for the content, such as recommending a warm color palette and realistic depiction for the Great Wall, as shown in Fig. 4.

4 Experiment

In this section, we focus on introducing the implementation details (Sec. 4.1), demonstrating comparison results of baselines (Sec. 4.2) and validate the effectiveness of our proposed LMM-based evaluation methods by qualitative, quantitative, and fidelity analyses (Sec. 4.3-4.5).

4.1 Implementation Details

We access GPT-4 and GPT-4V via the API. For T2I generation, we use SDXL v1.0 model ¹ and the official DALL-E 3 (OpenAI, 2023d) API of

¹https://huggingface.co/stabilityai/ stable-diffusion-xl-base-1.0 November 2023. We keep all hyper-parameters of the SDXL to their defaults. For DALL-E 3, we use its "hd" mode and set the image resolution to 1024×1024 . For LMM-based evaluation pipeline, we reset the system prompt of the GPT-4V to let it play the role of the interleaved content evaluator with a hint about subsequent jobs. 312

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4.2 Baseline Results on OpenLEAF

Tab. 3 presents the evaluation results of the GPT-4V-based agent system and its variants on the *Open-LEAF* set. Per-aspect scores are the average over all samples. The scores for the input-output interleaved sequences are only evaluated on problems with the corresponding image-text context. The overall score, an average of all 10 aspect scores, provides a comprehensive evaluation of the model's capability in the interleaved generation task.

In Tab. 3, we analyze three model variants that extend T2I prompt lengths and replace SDXL with DALL-E 3, aiming to examine how our evaluation pipeline can reflect these changes. Our analysis shows significant performance improvements of the agent system across most of the evaluated metrics with DALL-E 3, resonating the intuition that a better T2I model can lead to better interleaved results. Extending T2I prompts also improved scores in most aspects. However, longer T2I prompts did not enhance input-output attribute consistency. We hypothesize that more complicated T2I prompts might overload DALL-E 3's capability to accurately render attributes. These findings show that better T2I models and extended prompts effectively improve performance, validating the effectiveness of the *OpenLEAF* dataset and evaluation pipeline.

4.3 Qualitative Analysis

We conduct a qualitative comparison of interleaved content with high and low scores across each evaluation aspect. This analysis aims to determine whether our LMM-based evaluation pipeline effectively captures nuanced and comprehensive



Figure 5: The qualitative comparisons between the interleaved contents that yield high and low evaluation scores. Blue boxes highlight image regions that cause low scores on an evaluation aspect. Our detectionsummarization-scoring pipeline enables GPT-4V to understand both fine-grained and abstract image information, and give scores with logical rationales. Please zoom in to enjoy fine details.

multi-modal information, thereby providing scores backed by clear and logical reasoning.

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Output Interleaved Sequence Evaluation. Fig. 5 shows qualitative comparisons of output interleaved content across various dimensions. Our method effectively spots image artifacts, including blurring and text rendering flaws. In terms of aesthetics, it identifies issues like faded colors and lack of depth in image 3, alongside poor color variation and composition in image 4. For image-text coherence, the approach excels in aligning objects and highlighting mismatches, such as the absent human figure in image 2 and the incorrect final dish in image 4. This precision extends to identity consistency, where it reliably recognizes main characters and their inconsistencies. For style consistency, OpenLEAF discerns stylistic elements, correctly categorizing images based on predefined visual styles, showcasing its good capabilities.

Input-Output Sequence Evaluation. Fig. 6 il lustrates our method's effectiveness in evaluating
 input-output alignments for multi-modal queries
 and generated sequences. In assessing style con-

sistency, it identifies variations in media types and notes the cold tint in image 4 of the top sequence. For identity consistency, it precisely spots age differences in the fisherman across input and output images, highlighting its meticulous attention to detail. Attribute consistency evaluation captures subtle changes in the style of goggles. The evaluation of image-following capability points out minor atmospheric variances between input and output images in the upper example. Additionally, the assessment of input-output text alignment showcases the system's reliability in generating accurate ratings, confirming GPT-4V's ability to produce coherent texts that follow user directives.

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Collectively, the qualitative analyses in Fig.5 and389Fig.6 demonstrate the OpenLEAF's effectiveness390in identifying both specific and broad aspects of391multi-modal image-text content. OpenLEAF can392conduct comprehensive and adaptable evaluation393of interleaved content across different domains.394



Figure 6: The qualitative comparisons between the interleaved contents that yield high and low evaluation scores. Our evaluation pipeline is effective in capturing high-level input-output connections. Please zoom in to enjoy fine details.

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4.4 Quantitative Analysis

We conduct two types of quantitative evaluation to show the effectiveness of our LMM-based evaluation approach and analyze its behavior in comparison with humans. Our comparisons are based on 30 randomly selected interleaved content generated by our prompting-based interleaved generation baseline, which covers pure user query, user query with textual context, and image-text-conditioned generation scenarios. To collect human annotations, we conduct a user study and let human annotators give scores to each sequence for its image fidelity, image aesthetics, identity consistency, style consistency, and image-text alignment. We obtain 10 user responses in total for each sample. Next, we rank 30 samples on each aspect based on human scores, compared existing metrics (if available), and our evaluation scores. We report correlation scores of Kendall's τ and Spearman's ρ between the human rank and the rank by a compared evaluation method, indicating the similarity between the human annotation and the metric.

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Tab. 4 compares our evaluation approach with established VL-based metrics: CLIP, BLIP-ITM, and BLIP-ITC on image-text alignment evaluation. CLIP has the worst performance among all the compared metrics. BLIP-ITM and BLIP-ITC have higher correlation scores and lower p values, indi-

Metrics	Spear	rman's ρ	Kendall's τ		
Metrics	Corr↑	p-value↓	Corr↑	p-value↓	
CLIP (Radford et al., 2021)	0.2346	0.2206	0.1524	0.2576	
BLIP-ITM (Li et al., 2022, 2023c)	0.3444	0.0673	0.2692	0.0455	
BLIP-ITC (Li et al., 2022, 2023c)	0.3306	0.0799	0.2438	0.0701	
Ours	0.5066	0.0043	0.3609	0.0047	

Table 4: The rank correlation comparison on imagetext coherence between the established metrics and our evaluation approach. The correlation scores are obtained based on image ranks from the human annotation and the compared metrics. The best and the second best results are highlighted by green and orange backgrounds, respectively.

Evaluation Aspect	Spear	man's ρ	Kendall's τ		
Evaluation Aspect	Corr↑	p-value↓	Corr↑	p-value↓	
Image Fidelity	-0.0055	0.9767	0.2610	1.0000	
Image Aesthetics	0.2610	0.1637	0.1862	0.1547	
Image-Text Coherence	0.5066	0.0043	0.3609	0.0047	
Identity Consistency	0.3295	0.0754	0.2460	0.0581	
Style Consistency	0.4670	0.0093	0.2782	0.0314	

Table 5: The rank correlations between the human annotation and our evaluation approach on various aspects. The human annotation is obtained by a user study consisting of 30 interleaved image-text samples.

cating their superiority over CLIP. Our evaluation approach achieves the highest correlation score and lowest p value, signifying its superior alignment with human evaluations in image-text alignment. For the remaining evaluation aspects, since no existing metrics can be directly applied, we show the correlation analysis between our LMM-based evaluation with the human below.

In Tab. 5, we utilize Kendall's τ and Spearman's ρ to show the rank correlation between our LMMbased evaluation and human annotations across five evaluation aspects. The table reveals a strong alignment between our method and human judgment in assessing image-text coherence and style consistency, as evidenced by high correlation scores and low p values. However, there is a notable divergence in the evaluation of image fidelity, where the LMM-based approach shows lesser agreement with human annotations, leading us to conduct a more in-depth analysis of image fidelity.

4.5 Fidelity Analysis

In Fig. 7, we showcase two interleaved samples to illustrate differences in image fidelity evaluations between GPT-4V and human judges. The top sample is rated as the lowest in image fidelity by GPT-4V but considered intermediate by humans. Conversely, the bottom sample is deemed the worst by humans but one of the best by GPT-4V. This discrepancy arises from the differing criteria used



Human: 6.5 (Rank 1/30) GPT-4V: 10 (Rank 30/30) Rank from worst to best

Figure 7: The comparison between the contents favored by humans and GPT-4V on image fidelity. GPT-4V pays more attention on pixel-space image noise, blurry, editing errors, and distortions. Oppositely, humans focus more on semantic-level image artifacts.

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by GPT-4V and humans. GPT-4V concentrates on pixel-level details like noise, clarity, tone mapping errors, and gamma distortions. In contrast, humans focus more on semantic aspects of the images. For instance, in the bottom sample, humans notice semantic inconsistencies (e.g., an out-of-place face in the 3rd image), which GPT-4V overlooks. This divergence in focus and preference explains the low correlation between human and GPT-4V evaluations in terms of image fidelity. Recognizing that both perspectives offer valuable insights into image fidelity, we opt to retain the current fidelity evaluation prompt in our system and leave the humanaligned settings to be the future work.

5 Conclusion

In this paper, we focus on benchmarking the opendomain interleaved image-text generation by introducing an evaluation pipeline based on GPT-4V, a benchmark dataset to compare different approaches, and several baseline interleaved generation methods based on prompting GPT-4V and T2I models like DALL-E 3 and SDXL. Experimental results on the constructed benchmark dataset and a comprehensive analysis based on the user study demonstrates that the evaluation method based on GPT-4V can effectively evaluate the quality of an interleaved content in various aspects, where the evaluation pipeline, the benchmark dataset, and the baseline approach jointly form a reliable tool for benchmarking interleaved generative models.

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6 Limitations

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Unstable API Calls of GPT-4V. The presented 483 baseline method involves utilizing the DALL-E 3 484 API by OPENAI to transform Text-to-Image (T2I) 485 prompts into images. An observation is that the 486 DALL-E 3 API occasionally fails to generate im-487 ages for certain T2I prompts. This failure primarily 488 comes from the API's internal safety checks. Con-489 sequently, our baseline model may not be able to 490 generate interleaved content for certain queries. 491

Rating Variance. Another aspect worth discussing is the inherent variability in rating interleaved contents, especially for subjective aspects such as image fidelity and aesthetics. We aim at prompting GPT-4V to best mimic human evaluation processes when assessing interleaved content. As a result, its ratings also inherit a degree of variance akin to that of human evaluators. This variability positions GPT-4V's assessment more in line with subjective human judgment, rather than as a means of objective model-based evaluation.

7 Broader Impacts and Ethical Considerations

Broader Impacts. The introduction of *Open-LEAF*, a benchmark for the open-domain interleaved image-text generation task, represents a significant advancement in the field of multimodal content generation. By enabling the generation of content that seamlessly integrates both text and images, *OpenLEAF* paves the way for a myriad of novel applications. These include visual storybooks that can enhance learning and entertainment experiences, and detailed how-to instructions which could revolutionize education, technical manuals, and DIY guides by making them more accessible and engaging.

The ability to generate such integrated multi-518 modal content has the potential to significantly 519 impact industries such as education, publishing, and online content creation. For example, educational materials could be made more interactive 522 and tailored to individual learning styles, potentially improving learning outcomes. In the realm 524 of entertainment, personalized storybooks or inter-525 active guides could offer unique experiences that engage users in unprecedented ways. 527

528 **Ethical Considerations.** While *OpenLEAF* fo-529 cuses on the benchmarking aspect rather than the 530 generation process itself, it inevitably raises ethical considerations related to the deployment and development of AI technologies capable of interleaved image-text generation, especially for the proposed interleaved generation baselines. One of the primary concerns revolves around the integrity and authenticity of content. As AI models become more capable at creating realistic and coherent multimodal content, distinguishing between AI-generated and genuine content becomes challenging, raising issues of misinformation and trust. The concern about the integrity and authenticity of AI-generated content is a common issue for all generative models. 531

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Moreover, the benchmarking process itself must ensure fairness and avoid bias. The selection of datasets for evaluation and the definition of scoring criteria can inadvertently favor certain models or approaches. We have tried our best to ensure that *OpenLEAF*'s evaluation framework is designed to be as inclusive and unbiased as possible.

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A *OpenLEAF* Baseline Details

We present an agent system based on GPT-4V that can generate open-domain interleaved content in varying formats. Fig. 8 shows the results of our proposed baseline method in generating how-to instructions (top-left), visual stories (topright), and converting textual content into visual stories (bottom-left) and webpages (bottom-right) via HTML and CSS codes. In the remaining part of this section, we show more details of the proposed interleaved generation baseline method.

The system achieves open-domain interleaved generation based on GPT-4V (OpenAI, 2023c) and T2I models like DALL-E 3 (OpenAI, 2023d) and SDXL (Podell et al., 2023). The top panel of Fig. 9 shows the generation pipeline of our method. Given an arbitrary user query, we initially follow a meticulously designed composition strategy to assemble an input prompt that indicates the content, format, and constraints of the target output. We then feed the input prompt and the optional image-text context into GPT-4V, which generates the textual descriptions, determines the positions to insert images, and formulates the visual prompt for each image. Subsequently, we incorporate global entity and style contexts into the visual prompts to improve the entity and style consistencies of SDXL. Here, the entity context comprises the appearance descriptions of common subjects, while the style context is a unique image style description shared across all visual prompts. Finally, T2I models convert visual prompts into real images, thereby creating the interleaved content.

Prompt Composition. The input prompts to GPT-4V consist of four parts. We first add a few in-755 context examples at the beginning. Each example shows the desired output corresponding to a specific input query. The in-context examples enable GPT-4V to comprehend the expected content more 759 effectively and encourage it to generate content in the format of the in-context examples, facilitating easier automatic extraction of results. Subsequently, we concatenate the generation instruction 763 with the user input to form the prompt. In this 764 case, the instruction tells GPT-4V the desired out-765 put type, while the user input specifies the detailed content. Finally, we append control sentences to 767 specify the number of image placeholders, story sentences, instruction steps, and <div>s in HTML, 770 etc.

Text Generation. The first step of *OpenLEAF*

baseline is to generate text. By feeding the assembled prompt discussed in the previous part, we enable GPT-4V to produce all text descriptions and image placeholders, indicating the position of each image. For example, as shown in the text generation panel of Fig. 9, when generating stories and how-to instructions, GPT-4V is prompted to generate story sentences and instructional steps, respectively, where image tags <img{i}> is also included in the generated text. Each image tag indicates the position of the corresponding image, forming an initial interleaved structure. When generating HTML code, the position of each image is determined by the placement of the environment, where the generated CSS code can further tune the size, position, and alignment of each image. Next, we prompt GPT-4V to generate visual prompts from text descriptions. In this step, the input prompt also follows the composition strategy introduced earlier, incorporating all story sentences or instructional steps into the user input part. This approach allows GPT-4V to capture the context of the whole story or how-to instructions when generating the visual prompt for each image.

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Adding Global Context. To improve the entity and style consistencies of images within the interleaved content, we introduce global entity and style context into the visual prompts before feeding it into T2I models to generate images. For the global entity context, we add a short appearance description of each common subject to the visual prompts, where GPT-4V is used to extract common subjects from text content, generate appearance descriptions, and rewrite visual prompts. To improve the style consistency of images, we prompt GPT-4V to determine a proper visual style to depict the interleaved content, based on the generated text descriptions. For example, GPT-4V indicates that a vibrant color palette and comic book style are best suited to illustrate superhero stories. Then, a short image style description is added to the beginning of each visual prompt to control the artistic style of images generated by T2I models. Fig. 10 compares the images generated from T2I prompts with and without using global context. The global context encourages the generated images to have better identity and style consistencies. The visual prompts equipped with the global context are then converted into images by T2I models, resulting in the interleaved content.



Figure 8: **The open-domain interleaved content generation results by** *OpenLEAF* **baseline method.** We show results on producing visual how-to instructions (top-left), generating multi-modal stories (top-right), converting textual stories to multi-modal stories (bottom-left), and generating webpages and posters via HTML and CSS codes (bottom-right).

B Z-Score Analysis

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We conduct a Z-Score analysis to examine how closely the LMM-based evaluation mirrors human judgment and investigate GPT-4V's rating tendencies compared to human evaluators. We treat user ratings for each question as samples from an unknown distribution, estimating its mean and standard deviation (std) from these ratings. Then, we calculate the Z-Score for each GPT-4V evaluation and display these scores' distributions for each evaluation aspect in Fig. 11. On every aspect, most Z-Score's absolute values range within the [-std, std], suggesting that LMM-based scores align with human annotation distributions. However, we notice a slight positive bias in the Z-Score distributions for image fidelity, aesthetics, style consistency, and image-text alignment, indicating GPT-4V tends to rate these aspects higher than human evaluators. Conversely, the identity consistency aspect exhibits a higher std but a mean close to 0, suggesting that while GPT-4V's ratings align with human evaluations overall, there is greater variability in its scores.

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C User Study Interface

In Fig. 12 and 13, we show the interface for our846user study. We use the Google Forms to present847results to users and collect their responses. The first848page of the user study shows the guideline about849how to give scores for interleaved results on each850aspect. Then in other pages, users are given a set851of interleaved image-text results and we let users852



Figure 9: **Our interleaved generation framework.** The top panel illustrates the overall framework while other panels show details of each procedure.

to give score on each aspect based on the presented results.

D OpenLEAF Dataset Examples

The evaluation dataset of *OpenLEAF* contains 660 generation problems, which are categorized into three types according to the input format: user query only, user query with textual context, and user query with image-text context. In the following, we show a few questions for each input format and topic. The full evaluation set will be released together with the baseline and evaluation codes.

D.1 User Query Only

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In this part, we show example problems in *Open-LEAF* evaluation set that only contain user queries in the input.

Cooking and Recipes (How-to) This group represents a category with a high frequency of realworld queries, is versatile, and is relatable for many people. • How do you make a classic French ratatouille?

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- What are the steps to prepare and cook a beef Wellington?
- How can you make vegan chocolate chip cookies without eggs?
- What's the process to ferment your own sauerkraut at home?
- How do you prepare a traditional Spanish paella with seafood?

Story Requests about Specific Characters (**Story**) This group captures the essence of storytelling with recognizable characters, allowing for the evaluation of creativity and fidelity to known character attributes.

• Can you narrate a story where Sherlock Holmes solves a mystery in modern-day New York?



Figure 10: The comparison between images generated from T2I prompts with and without using global context. Using global context significantly improves the identity and style consistencies of images in the interleaved content.



Figure 11: The Z-Score analysis of *OpenLEAF* evaluation against human annotations. *OpenLEAF* evaluation scores mostly fit the $1-\sigma$ range of the human's score distribution.

 How about a tale where Cinderella decides to start her own shoe business?

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- What happens when Thor decides to take a break from being a god and lives as a common man on Earth?
- Tell a story about Snow White becoming an advocate for environmental conservation.
- How does James Bond handle an assignment when all his gadgets fail?

Travel and Places (How-to) This group represents a wide range of possible tasks, from planning trips to learning about world cultures, which is relevant to many users.

- How do you plan a two-week road trip across the U.S. Route 66?
- What are the top 5 recommended places to visit in Kyoto, Japan?

- How to pack efficiently for a 909 month-long backpacking trip across 910 Europe? 911
 What are the must-see landmarks when 912
- What are the must-see landmarks when visiting Rome, Italy?

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• How do you ensure safety while traveling solo in South America?

Fitness and Well-being (How-to) With an increasing focus on health and well-being globally, this category helps evaluate responses that touch upon both physical and mental well-being.

- How do you create a balanced weekly workout routine for weight loss?
- What are the steps to mastering the crow pose in yoga?
- How to develop a mindful meditation practice for stress relief?
- What's the best way to start a ketogenic diet for beginners?
- How do you build endurance for running a marathon?

Story Requests about General Subjects (Story) This group offers a more generic and flexible storytelling approach, allowing for the creation of new and diverse stories based on common subjects.

• Can you tell a story about a raindrop's journey through the water cycle?

Interleaved Image-Text Generation Quality Assessment

In this user study, you will be presented with 30 sets of interleaved image-text content. For each set, you will view a user's request to generate this interleaved content, which may include input images to offer visual hints about the desired outcome. Following this, you will be asked several questions assessing the quality of the interleaved content. Each question will come with multiple-choice options; please select the one you believe most accurately reflects your opinion.

Evaluation Rubrics

Here are the questions you will be asked when evaluating the quality of an interleaved content. For each question, please choose 10 if it is perfect, 5 if the result is good overall but have minor issues, and 0 if the result is bad.

* * *

1. Image Fidelity: Does each image artifact-free? Artifacts means the undesirable or unexpected alteration or distortion in an image, making the presentation of the content or semantics of the image incorrect. Image style should not be considered in evaluating.

2. Image Aesthetics: Does each image aesthetically good?

Image-Text Coherency: In the interleaved content, each image should be coherent with its preceding Text/Sentence.
 Entity Consistency: Do the main subjects/objects of the interleaved content have consistent appearance among all images? When making evaluation, image style should not be considered.

5. Style Consistency: Do all images in the interleaved content have consistent image styles. <u>When making evaluation</u>, image content should not be considered.

6. Output Text Quality: Does the text in the output content align well with the input request? When making evaluations, please focus on texts and overlook images.

7. Input-Output Image Entity Consistency: Do the main subjects/objects of the interleaved content have consistent appearance between the input and output image? <u>When making evaluation, image style should not be considered.</u>
8. Input-Output Image Attribute Consistency: Do the main subjects/objects of the interleaved content have consistent attribute between the input and output image? Attribute is designated by the text attached with the input image. <u>When</u>

<u>making evaluation, image style should not be considered.</u> **9. Input-Output Image Style Consistency**: Do the input and output images have consistent image styles. <u>When making evaluation, image content should not be considered.</u>

10. Input Image Following: Considering a new interleaved content by replacing the Output Image 1 with the Input Image 1. Does the Input Image 1 coherent with Output Image 2 and its subsequent images?

Figure 12: The evaluating guideline of the user study.

 Can you weave a tale about a tree that has witnessed centuries pass by?

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- What's the story of a lonely lighthouse on a remote island?
- Can you narrate a tale of a mysterious mirror that shows one's true self?
- How about a story where the wind is a mischievous character playing tricks on a town?

Home Improvement and DIY (How-to) Given the prevalence of DIY and home improvement projects, this category tests practical advice and steps on common household projects.

 How do you install a floating shelf without visible brackets? 	950 951				
• What are the steps to refinish an old wooden table?	952 953				
 How can you soundproof a room effectively for a home theater setup? 	954 955				
• What's the process to properly lay ceramic tiles in a bathroom?	956 957				
 How do you create a vertical garden wall in your balcony? 					
Arts and Crafts (How-to) Creative in nature,	960				

Arts and Crafts (How-to) Creative in nature, this category evaluates the generation of artistic and craft-related content.

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The image on the right defines the expected appearance of entity [Bard] for the generated images.		The image on the right defines the expected appearance of entity [Dragon] for the generated images.	CE CONTRACTOR		Score: 0	Score: 5	Score: 10	[For Q7-Q10] Not ap
				Image Fidelity				
XIX	Call Start			Image Aesthetics				
	MA SAN			Image-Text Coherency				
		RAL	1961	Entity Consistency				
Sentence 1: In a realm of ancient castles and mythical	Sentence 2: Wandering through mystical lands one	Sentence 3: The dragon, enchanted by the bard's melodies, revealed a soft spot	Sentence 4: Word of the bard's magical encounter spread	Style Consistency				
creatures, there lived a nomadic bard, distinguished by his majestic beard and decked in	eve, the bard, under the silvery embrace of the moon, encountered a magnificent dragon	reveated a sort spot for music. Astonishingly, the creature was gentle and humble,	throughout the medieval kingdom, unveiling the dragon's tender soul that music unveiled.	Output Text Quality				
a lavish robe. His eyes gleamed with the wisdom of the world, and his	with scales as dark as the night and eyes that shone like twin stars. The	contrasting the fierce and tyrannical image dragons were famed	Bound by an inseparable bond, they roamed the kingdom together.	Input-Output Image E				
hands, skilled and nimble, strummed magical melodies on a lute, echoing the enchanting rhythms of life.	dragon's majestic wings were spread out, powerfully illuminating the	for. Every chord struck by the bard, weaved a mystical bond between them, a	singing ballads of magical realms. The feared beast, once a symbol of terror.	Input-Output Image S				
	serene elegance and the feared yet revered majesty of the creature.	symphony of serenity amidst the wilderness, harmonizing the	became emblematic of magical collaborations, as music - the unifying	Input-Output Image A				
		terrorizing roars into melodic hums.	song of the spheres - harmonized different worlds.	Input Image Following				

Figure 13: The visualization of result and the evaluation panel in the user study.

963 964 965 966	 How can you create a mosaic art piece using broken ceramics? What are the steps to knit a cozy winter scarf for beginners? 	 Gardening and Plant Care (How-to) This category can test for accuracy and depth of knowledge on a topic that many people are passionate about. How can you grow tomatoes in a containing wander? 	988 989 990 991
967 968	 How do you craft a homemade greeting card with 3D pop-up details? 	container garden?What's the process for propagating succulents from leaves?	992 993 994
969 970	 What's the process to sculpt a miniature clay figurine? 	 How do you care for orchids to ensure they bloom annually? 	995 996
971 972	 How can you make DIY jewelry using beads and wires? 	• What are the steps to prepare garden beds for spring planting?	997 998
973 974	Myths, Legends, and Historical Tales (Story) This group focuses on retelling or crafting stories	 How can you cultivate roses to produce vibrant blossoms? 	999 1000
975 976	from the past, ensuring that the model's output adheres to known historical or mythical details.	Adventure and Exploration (Story) Pushing the boundaries of creativity, this category allows for the creation of new, exciting, and engaging	1001 1002 1003
977 978	• Can you recount the legend of King Arthur and the Knights of the Round	stories centered around adventure themes.	1004
979 980	Table? • What is the story behind the Trojan	 Can you weave a tale about an explorer discovering a hidden city beneath the Sahara Desert? 	1005 1006 1007
981	Horse in ancient Troy?	 What's the story of a young woman navigating the treacherous waters of 	1008 1009
982 983	 How did Icarus fly too close to the sun in Greek mythology? 	the Amazon River?How did a group of adventurers uncover	1010 1011
984 985	 Can you narrate the tale of Cleopatra and her influence over Rome? 	a secret entrance to Hollow Earth?	1012
986 987	• What is the legend of the Lost City of Atlantis?	 Can you narrate a tale of an astronaut stranded on an alien planet and their journey back home? 	1013 1014 1015

 What's the chronicle of a mountaineer 1016 attempting to scale an unclimbed peak 1017 in the Himalayas? 1018

D.2 User Query with Text Context

In this part, we show example problems in Open-LEAF evaluation set that contain textual context in the input.

Animal Stories

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- In a verdant meadow, a rabbit often 1024 about how fast it could boasted run. Challenged by a tortoise, 1026 1027 the overconfident rabbit took a nap midway through the race. The diligent 1028 tortoise, never pausing, continued 1029 1030 its steady pace to cross the finish line first, proving that persistence 1031 often trumps speed. 1032
- Perched high in a tree, a wise old 1033 owl observed the other birds chatter 1034 and squabble throughout the day. When 1035 asked why he was so silent, the owl 1036 replied, "The more I watch and listen, 1037 the more I learn. Sometimes silence 1039 teaches us more than noise."
- 0n the banks of а tranquil 1040 pond. а proud swan, mesmerized 1041 own reflection, 1042 by its dismissed 1043 the drab-looking ducklings nearby. However, as seasons changed, those 1044 ducklings matured into magnificent 1045 swans, illustrating that beauty often lies hidden beneath the surface. 1047
- jungle, • Deep in the а peacock 1049 displayed its vibrant feathers, catching the envy of other animals. 1050 Yet, when a heavy rainstorm hit, it 1051 1052 was the humble sparrow, with its modest plumage, that found shelter 1053 and stayed dry, highlighting that outer beauty doesn't always provide 1055 inner strength. 1056
- Near bustling anthill, 1057 а а 1058 grasshopper spent its days singing While the ants toiled, and dancing. 1059 storing food for winter, the 1060 grasshopper mocked their diligence. Yet, when winter came, the ants were 1062

well-prepared,	and	the	grasshopper,	1063
regretting its	lazir	ness,	went hungry.	1064

Brand Introductions

- Title: Who is Nikon? Content: 1066 Nikon Corporation is а Japanese 1067 multinational corporation 1068 specializing in optics and imaging 1069 Founded in 1917, Nikon products. 1070 has established itself as a global 1071 leader in camera lenses, binoculars, 1072 and microscopes. Known for producing high-quality DSLRs, it has been a 1074 among photographers for favorite 1075 generations. 1076
- Title: Who is Oracle? Content. 1077 Oracle Corporation is an American 1078 multinational computer technology 1079 company. Since its inception 1080 in 1977 Larry Ellison, Bob by 1081 Miner, and Ed Oates, it's provided 1082 cloud solutions, software, and 1083 hardware products, with its primary 1084 focus being databases. Oracle serves both the business and enterprise sectors with its vast range of 1087 services.
- Title: Who LEGO? is Content: is LEGO Group Danish а tov 1090 production company known globally 1091 for its iconic interlocking plastic 1092 Established in 1932 by bricks. 1093 Ole Kirk Christiansen, LEGO has expanded its realm, creating movies, 1095 games, competitions, and six themed 1096 amusement parks. 1097
- Title: Who is Ubisoft? Content: 1098 Ubisoft Entertainment SA is a French 1099 video game company headquartered in 1100 Founded in 1986, Montreuil. it's 1101 the largest in the now one of 1102 Renowned for franchises industry. 1103 like Assassin's Creed, Far Cry, and 1104 Just Dance, Ubisoft continues to 1105 deliver immersive gaming experiences. 1106
- Who is Panasonic? • Title: Content: 1107 Panasonic Corporation is a Japanese 1108 multinational electronics company 1109 founded by Konosuke Matsushita in 1110

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11111918. Initially a lightbulb socket1112manufacturer, it has grown into one1113of the largest Japanese electronics1114producers, alongside Sony, Hitachi,1115Toshiba, and Canon.

D.3 User Query with Image-Text Context

1117In this part, we show example problems in Open-1118LEAF evaluation set that contain image-text con-1119text in the input.

One Image Indicating the Identity This group contains one image per question that indicates the appearance of the main identity of the target interleaved content.



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User Input: How to brew the perfect cup of herbal tea?

The image on the right defines the expected appearar of main entity fo the generated

The image on the right defines the expected appearance of main entity for the generated images.



User Input: Can you write a story about a lonely lighthouse keeper and a mysterious ship that appears every night?



User Input: Can you craft a tale about a time-traveling librarian who seeks a forbidden book in ancient Alexandria?

age on the defines the ed appearance terated



User Input: Can you narrate an adventure of a robot and a hummingbird who explore the ruins of a forgotten city?



Dual Image Indicating the Identities This group contains two images per question that indicating the appearance of the two main identities of the target interleaved content. User Input: Can you spin a tale about a young witch and her talking raven companion?



User Input: Can you weave a narrative of a stranded astronaut and a benevolent alien on a distant planet?





User Input: Can you narrate a story of a treasure hunter and a mermaid exploring sunken ruins?





User Input: Can you describe a tale of a nomadic bard and a dragon who loves music in a medieval kingdom?

image on the ht defines the ected appearance entity [Bard] for generated ges.



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User Input: Can you detail a journey of a robotic engineer and a sentient AI navigating a post-apocalyptic world?

The image on the right defines the expected appearance of entity [AI] for the generated images.



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One Image Showing the Image Style This	1138
group contains one image per question that indicat-	1139
ing the visual style of the target interleaved content.	1140
User Input: Can you weave a story about a clockmaker who discovers a hidden world within one of his creations?	

The image on the right defines the expected image style of the generated images.



User Input: Can you narrate a tale about a detective with the ability to hear the last words of the deceased? The jagg on the right defines the expected jage style



User Input: Can you recount an adventure about a pianist who can bring inanimate objects to life with her melodies?

image on the t defines the tcde image style he generated es.



User Input: Can you describe a narrative involving a graffiti artist whose paintings predict future events?



User Input: Can you craft a story about a gardener w plants seeds that grow into portals to other dimensions?





One Image Showing the Attribute This 1146 group contains one image per question 1147 that indicating the appearance of a specific 1148 1149 attribute of the target interleaved content. User Input: Can you tell a tale about a mountaineer who finds a hidden city atop a peak?



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User Input: Can User Input: Can you weave a story of a potter whose clay sculptures come to life during a full moon?

e image on the ght defines the bected appearance attribute otter's wheel] for e generated



User Input: Can you narrate an account of a fisherwoman who captures a talking fish that offers three wishes? User Input: Can vou

he image on the ight defines the xpected appearance if attribute Fisherwoman's hat] or the generated



User Input: Can you unfold a tale about a writer whose fictional characters start appearing in the real world?



User Input: Can you relay discovers a floating isla narrative of a pilot who



One Image Showing the First Image This group contains one image per question that showing the first image of the target interleaved content. User Input: Can you weave a tale about a librarian who discovers a book that writes its story in real-time?



User Input: Can you describe a narrative involving a gardener whose plants hum tunes from old legends



Input: Can you craft a story about a chef who can taste people's emotions in the ingredients they touch?



User Input: Can you narrate a tale of a jeweler who creates amulets that grant the bearer's hidden desires?





User Input: Can you recount an adventure of a tailor whose stitched clothes reveal the future of those who wear them?





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Extra Interleaved Generation and E **Evaluation Results with the OpenLEAF Baseline**

In this section, we first show two generation (Fig. 14 and 17) and raw evaluation outputs (Fig. 15, 16, 18, and 19) of our OpenLEAF baseline and evaluation approach, respectively. Taking Fig. 14 as an example, from the top to bottom, we show the user query at the top of the figure. Underneath it, we present the input images, if available, and state how the generated interleaved content should correlate with the input images. Next, we show all images and textual sentences from the generated interleaved content. For the raw evaluation outputs as shown in Fig. 15 and 16, we demonstrate the evaluation results including the score and the justification in each evaluation aspect, where the image quality includes the image fidelity and aesthetics. In each aspect, we follow the detection-summarization-scoring pipeline and show the evaluation output of each round one-byone. We then show more interleaved generation results by the OpenLEAF baseline model in Fig. 20 to 29. We use DALL-E 3 for T2I generation in the interleaved content creation. The above figures demonstrate that OpenLEAF can produce highquality interleaved content with coherent imagetext sequence following the multi-modal context provided by users. The OpenLEAF evaluation outputs can capture fine-grained and abstract image details and give reasonable scores and clear justifications.

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User Input: Can you conceive a narrative about an architect who designs buildings that heal the environment?

The image on the right defines the expected image style of the generated images.





Sentence 1: In a world suffused with hues of amber and azure, there lived an architect whose vision extended beyond concrete structures. Surrounded by landscapes treated as beautiful puzzles, the architect was inspired to breathe vivid life into his designs. Every blueprint he crafted possessed a symmetry and balance echoing nature's elegance. Sentence 2: One day,

amidst the harmonic dance of shadow and light, a revelation sparkled in the architect's mind. A concept of buildings become photosynthesizing entities, drawing toxins from the air and injecting oxygen back into the cities, where geometric lines met fluid grace.



Sentence 3: The architect had a gift for marrying straight angles with eloquent curves. His masterpiece: a structure where metal and glass spiraled upwards, mimicking the ascent of hot air balloons, breaking the monotony, and filling the skyline with colors reminiscent of a painting brushed by the fingers of twilight and dawn.



Sentence 4: As the transient sunlight glistened off the stained-glass extensions of the pinnacle, the architect's building stood as a testament to harmony. Between mankind and nature, it pulled the toxic whispers from the air and breathed out an aurora of healing echoes. A single edifice, yet it painted a future where architecture didn't just coexist but flourished midst nature's embrace.

Figure 14: The generated interleaved content by the OpenLEAF baseline method.

designing, and re	score of 10. The text a	ontribute positively t		ach step in the text provides ent. The narrative flows coher			
<pre>inout_style_consi Round 1:</pre>	stency						
Output Image 4 (p	ainting, colorful) 			ainting, colorful) Output Im			
Media Type (rea painting		n) painting		painting polychromatic	painting polychr		painting
Tint (warm, col	po	lychromatic w	1	porychromacic	porychi	warm	I
warm Saturation (hig		h		high		high	
high			5				
Round 2:							
Aspect 				t - Output Image 3 Input - O 	0utput Image 4 		
	10 10 10	10 10	10 10	10 10			
Tint Saturation	10 10	10 10	10 10	10 10			
Round 3:							
 Media Type: (1 Color Palette: Tint: (10+10+1 Saturation: (1 Final score: 	0+10+10+10)/4 = 10						
(10+10+10+10)/4 = In conclusion, th	e style consistency scor	e between the input im	age and each o	f the output images is a perfe	ect 10. This indicates that	there is excellent (consistency in terms
	ligning perfectly with th			ented. All images exhibit a pa	inting style with high sat	uration, warm tint, :	and polychromatic
	Image 1		Image 2		Image 3		Image 4
li '					-	1	
 Media Type			Painting		Realistic		Painting
1	Polychromatic		Polychromatic		Polychromatic		Polychromatic
1	Warm		Warm		Warm		Warm
 Saturation	High		High		High		High
T	-		-		-		-
Round 2: - Media Type Cons - Color Palette C - Tint Consistenc - Saturation Cons	ionsistency: 10 sy: 10						
Explanation:							
- The color palet - All images have	te consistency is good a a warm tint which is co	cross all images, they nsistent throughout th	all are polyc e interleaved	and one is more realistic. hromatic. content.			
- Saturation is a Round 3:	lso consistent, with high	activitient i	in act images.				
	10+10+10)/4 = 8.75						
The style consist tint, and saturat		erent visual aesthetic	ontent is 8.75 s.	. Despite minor inconsistencie	s in media type, the image	s maintain consisten	cy in color palette,
<pre>image_text_cohere 1. **Step 1 and I</pre>	mage 1:** The image fits the ambiance of a world Content: None	the description perfe	ctly. It portr amber and azu	ays an architect surrounded by re", and the architect appears	r vivid, lively, abstract n ; to be inspired and in awe	ature-inspired depic [.]	tions. There are
who is presumably nature-infused ar - Mis-matched	the architect, staring a chitecture but doesn't d Content: The photosynthe	at a futuristic, vibra irectly imply the buil sizing effect of the b	nt cityscape t dings' photosy uildings is no	come entities drawing toxins a hat reflects the harmony of fl nthesizing ability. t visually evident. though the specific element of	uid grace and geometric li	nes. It visualizes t	image captures a man ne concept of
	iniscent of twilight and Content: None			th each other. The text speaks d beautifully captured in the		etal and glass spira	l upwards, with a
which is not visu beautifully integ - Mis-matched - Coherency Sc	ally evident. However, the prated with nature. Content: The building's a core: 5 (The primary conce	he image does illumina ability to pull toxins	te the stateme and breathe o	s as a testament to harmony, p nt about the transient sunligh ut healing echoes is not depic and nature is evident, but spe	nt glistening off the glass rted.	, showing a building	intricately, and
lacking visually. The overall conte essence of each s		tches where conceptual ensuring the expressi	descriptions on remains coh	in the text are not directly v erent.	risually represented in the	interleaved images,	but the core

Figure 15: The raw evaluation output for the generated interleaved content (Fig. 14) by the *OpenLEAF* baseline method.

entity_consistency Round 1: The major subjects that are recognizable in the given interleaved content through the steps/sentences and images are the "architect" and the "architect's buildings with nature-inspired designs." Round 2: **Architect:**
 Image 1: The architect is presented with a clear, detailed, and distinct appearance. He is shown holding blueprints, embodying the essence of his profession.
 Image 2: The entity consistency is moderately held, though the architect's features are not as distinct. The focus shifts towards the buildings and the fusion of nature and architecture.
 Image 3: The architect is not visible. The focus is on the building manifesting as a result of the architect's innovative design vision.
 Image 4: Like Image 3, the architect is not seen. Concentration is on the portrayal of the building. 2. **Architect's Buildings with Nature-Inspired Designs:** - **Image 1:** Nature's elegance is expressed using vivid, abstract art but no buildings are depicted. - **Image 2:** The buildings become pronounced with nature-inspired designs, leading to a clear entity consistency with the textual content. - **Image 3:** The building's design, inspired by nature, is prominent and aligns with the narrative. - **Image 4:** The completion of the architect's vision is captured well, showing a building in harmony with nature. Round 3: 1. **Architect:** - Entity Consistency Score: 5 - Explanation: There is a shift from a clear presentation of the architect to a more conceptual visualization, and in Images 3 and 4, the architect is not visible. **Architect's Buildings with Nature-Inspired Designs:**

 Entity Consistency Score: 10
 Explanation: Despite the gradual evolution from the conceptual introduction of nature-inspired designs to clear visual presentations in latter images, the theme remains consistent.

 Note: The scores are allocated considering the variations and consistencies in depicting these two primary entities. While the architect's physical presence diminishes, the continuation of his vision through nature-inspired architectural designs is evident and consistent throughout the images. image_quality
Task 1: Image Fidelity Evaluation #### Image 1 - **Artifacts:** Nome noticeable - **Score:* 10 - **Explanation:** The image appears clear without any noticeable artifacts or distortion, maintaining a high fidelity visual presentation. ### Image 2
*#Artifacts:** None noticeable
Score: 10
Explanation: There is no visible alteration or distortion that negatively impacts the semantics of the image or its quality. The image expresses the content clearly. #### Image 3
- **Artifacts:** None noticeable **Artifacts:-- moule involvence **Score:** 10 **Explanation:** Image 3 is artifact-free, with seamless blendings of different elements, resulting in a high-quality depiction. #### Image 4 - **Artifacts:** Nome noticeable - **Score:* 10 - **Explanation:** Like the others, Image 4 also has a visual presentation. No significant artifacts can be identified and it aligns well with a high fidelity. #### Image 1 - **Score:** 10 - **Explanation:** A visually captivating composition, characterized by exquisite detail, vibrant colors, and abstract nature-inspired elements which add a strong aesthetic appeal. #### Image 2 - **Score:** 10 - **Explanation:** This image offers a striking aesthetic appeal, showcasing a harmoniously intricate design, dazzling colors, and a beautifully illuminated cityscape. #### Image 3 - **Score:** 10 - **Scoper:* 10 - **Explanation:** With a breathtaking contrast of warm and dynamic colors amidst the serenity of the sky, and the innovative design of the building, this image possesses exceptional aesthetic value. #### Image 4 - **Score:** 10 - #*Explanation:** The spectacular blend of colors reflecting off the building, coupled with the finely detailed architecture and radiant lighting, encapsulates a scene of magnificent aesthetic beauty. ### Summary The images are all artifact-free, offering clear, high-quality visual content. They hold significant aesthetic value characterized by vibrant colors, intricate designs, and creative compositions that are both visually pleasing and emotionally evoking. The artistic and aesthetic synergy in the images exemplarily complements the textual context, reinforcing the narrative flow and thematic coherence within the interleaved content.

Figure 16: The raw evaluation output for the generated interleaved content (Fig. 14) by the *OpenLEAF* baseline method.

User Input: Can you craft a story about a chef who can taste people's emotions in the ingredients they touch?

The image on the right defines the expected first image for the generated images.





Sentence 1: In the bustling kitchen of a renowned restaurant, a talented chef with a meticulously groomed beard was known for creating unimaginable flavors. He discovered his extraordinary gift when he tasted a pinch of the sauce he was preparing and immediately experienced a wave of emotions. Sentence 2: The chef

Sentence 2: The chef realized that his unique ability allowed him to taste the emotions of the people who touched the ingredients. Each dish unveiled a story, a clandestine chapter of the lives intertwined with every flavor and aroma.



Sentence 3: Word spread about the empathetic chef, and people from far and wide visited his restaurant. They were curious and eager to taste dishes that mirrored their innermost emotions, eliciting tears of joy, laughter, and sometimes, silent reflections.



Sentence 4: The chef's extraordinary talent turned the restaurant into a sanctuary, where guests embarked on journeys of selfdiscovery through every bite. Food was no longer just a meal, but a profound experience of emotional revelation and unison of souls.

Figure 17: The generated interleaved content by the OpenLEAF baseline method.

Inout text quality I would give a score of 10, as the text in the output content aligns well with the input request. The output content adheres to the prompt by depicting a story about a chef who can taste people's emotions through the ingredients they touch. Each step of the output content expands the narrative effectively, making it cohesive and directly related to the request.
inout following To evaluate the potential replacement of Output Image 1 with Imput Image 1, let's examine the coherence and quality of this new interleaved content.
Input Image 1 depicts a chef who appears to be in a state of surprise or curiosity as he tastes something, with a busy kitchen sceme as the backdrop. The potential incompatibility or coherence issues would arise depending on how well this image aligns with the accompanying text and subsequent images.
- Does the Input Image 1 coherent with Output Image 2 and its subsequent image?
In terms of the visuals, Input Image 1 aligns fairly well with Output Image 2, where the chef is depicted in a moment of realization about his unique ability to taste emotions. The surprise and curiosity expressed in Tnput Image 1 could complement the dramatic explosion of flavors and emotions depicted in Output Image 2; the sequence of emotions from curiosity to realization is visually logical.
On the continuity with subsequent images, Input Image 1 may slightly deviate. It effectively communicates the chef's astonishment or curiosity but might not carry the otherworldly or transcendental quality that seems inherent in later images, especially Output Image 4. In this context, the original Output Image 1 does a better job of introducing that mystical experience.
- Does the new interleaved content have good image-text coherency? Considering the text, the replacement of Output Image 1 with Imput Image 1 might not align perfectly with Step 1's description of the chef experiencing a wave of emotions.
Input Image 1's surprise expression doesn't necessarily communicate a profound emotional revelation the same way Output Image 1 does. But. it could still work decently, as only a part of the emotional wave of experience would seeminoly be missed. The bustling kitchen background in Input Image 1 certainly
complements the textual description of the kitchen scene. Given these considerations:
- Input Image 1 can somewhat fit into the space of Output Image 1 in visual and emotional progression.
- The kitchen backdrop in Input Image 1 aligns well with the text. - The emotional and mystical quality is slightly compromised.
I would assign a score of 5. The new interleaved content has minor issues, but it still maintains a good level of coherence for most audiences. The image can depict the onset of the off's realization of his gifts but may not convey the profound depth of emotions as effectively as the original Output Image 1.
Round 1: Summarize the visual style of each image
Aspects Image 1 Image 2 Image 3 Image 4
Media syme (realistic, painting, cartoon) painting painting painting painting **Color Pairte (monochromatic, polychromatic)** polychromatic polychromatic polychromatic polychromatic **Tint (warm, cold)** warm
Round 2: Score on the style consistencies of each aspect
Aspects Score (0,5,10)
Mcdia type 10 **Color Patent** 10 **Tint** 10
Every image has been illustrated with a painting media-type, has a polychromatic color palette, holds a warm tint, and shares a high level of saturation.
Round 3: Final Score of the Style Consistency
(18+18+18+18)/4 - **18**
Explanation:
The interleaved content achieves a perfect score of 10 for style consistency. Each of the aspects, namely media type, color palette, tint, and saturation, are consistent throughout the four images shock-add in the content. Every illustration is a painting featuring a polychromatic color palette, warm tints, and high saturation. This consistency in style allows for a cohesive and visually harmonius reader experience, emhancing the impact of the interleaved content.
image text, coherency mer image i The period of the second
Discovered Mis-matches: No mis-matched elements found.
Score on Image-Text Coherency:
10 #### Explanation: The image accurately reflects the chef in his busy kitchen tasting a pinch of the sauce and experiencing a wave of emotions. His astonishment matches the text description.
<pre>sest Enage 2 sest Fraceding Text/Sertence: The chef realized that his unique ability allowed him to taste the emotions of the people who touched the ingredients. Each dish unveiled a story, a clandestine chapter of the lives intervined with nevery llavor and aroma.</pre>
Discovered Mis-matches:
No mis-matched elements found. #### Score on Image-Text Coherency:
10 #### Explanation:
The image represents the chef's realization of his unique ability vividly. The burst of colors and dynamic elements effectively portray the mix of emotions and stories unveiled through every flavor and aroma.
<pre>*** Inage 3 *** Preceding Text/Sentence: Word spread about the empathetic chef, and people from far and wide visited his restaurant. They were curious and eager to taste dishes that mirrored their innermost encions, eliciting tears of joy, laughter, and sometimes, silent reflections.</pre>
Discovered Mis-matches: The image does not depict the visitors' reactions in terms of tears of joy, laughter, or silent reflections as expressed in the text.
Score on Image-Text Coherency: 5
Explanation: The image depicts people gathering around the chef due to his reputation, in alignment with the text. However, it does not illustrate the various emotional reactions elicited by the tasting of the dishes, as described in the text.
<pre>resplace 4 eresplaceding Text/Sentence: The chef's extraordinary talent turned the restaurant into a sanctuary, where guests embarked on journeys of self-discovery through every bite. Food was no longer just a meal, but a protound experience of emotional revelation and unison of souls.</pre>
Discovered Mis-matches: No mis-matched elements found.
Score on Image-Text Coherency:
10
Explanation: The image effectively captures the guests experiencing emotional revelations and unity through their meal, epitomizing the sanctuary-like ambiance of the restaurant due to the chef's talent.
<pre>### Overall Assessment: The coherency between the images and their preceding text is significantly strong. Three out of four images perfectly match the adjacent text, demonstrating an evident correlation. One image has minor inconsistencies as it doesn't capture the range of emotional reactions described in the text but still aligns with the overall sentiment and narrative. The seamless connection between the image and text iterations amplifies the potency and evocativeness of the interleaved content.</pre>

Figure 18: The raw evaluation output for the generated interleaved content (Fig. 17) by the *OpenLEAF* baseline method.



Figure 19: The raw evaluation output for the generated interleaved content (Fig. 17) by the *OpenLEAF* baseline method.

User Input: Can you craft a story about a gardener who plants seeds that grow into portals to other dimensions?

The image on the right defines the expected image style of the generated images.





Sentence 1: In a quaint village silhouetted against the intricate dance of twilight shadows, a gardener planted seeds with hands, both rough and tender, shaped by years of nurturing life.



Sentence 2: One moonlit night, amidst the symphony of rustling leaves, something miraculous occurred; the seeds blossomed into portals, delicately intricate yet exuding an indomitable essence.



Sentence 3: The gardener, with wisps of gray hair reflecting the moon's gentle glow, bravely stepped through one, unveiling a realm where fantasies were not birthed, but lived, a universe painted with strokes of magic beyond human comprehension.



Sentence 4: Eventually, each portal offered solace, adventures, and lessons; casting ripples of change, not just through the reminiscent echoes of the timeless village, but etching immortal imprints upon the soul of the humble gardener.

Figure 20: The generated interleaved content by the OpenLEAF baseline method.

User Input: Can you craft a tale about a time-traveling librarian who seeks a forbidden book in ancient Alexandria?

The image on the right defines the expected appearance of main entity for the generated images.





Sentence 1: In a world overwhelmed by digital screens and artificial intelligence, a librarian with dark, short hair and clad in a long black coat, sought refuge in books and scrolls. Tucked within the anonymous corridors of a modern library, they discovered an ancient text that hinted at a forbidden book that possessed knowledge to transcend time and space.



Sentence 2: Consumed with curiosity, the librarian got hold of a peculiar metallic device inscribed with cryptic symbols from the realm of antiquities. As they adjusted the dials, a vortex of light spiraled, and they found themselves amidst the grandeur of ancient Alexandria, surrounded by intricate architecture and scrolls detailing the world's oncelost knowledge.



Sentence 3: The librarian, out of place amidst the grandeur of the ancient library, utilized their modern intellect and ancient texts, becoming engulfed in a cat-and-mouse chase through the towering shelves and architectural marvels of the space. The black coat swirled around them as they navigated the complexities of a civilization ahead of its time.



Sentence 4: As the distant roars of the ancient city echoed through the halls, the librarian with the dark, short hair clutched the forbidden book against the black fabric of their coat. Amidst the text lay secrets that could change the fate of timelines intersected. As they stared at the cryptic symbols found earlier, the vortex reappeared, paving the ascension to a world where past, present, and future became one.

Figure 21: The generated interleaved content by the OpenLEAF baseline method.

User Input: Can you depict a tale centered on a zookeeper who understands the secret language of animals?

The image on the right defines the expected first image for the generated images.





Sentence 1: In the tranquility of the night, under the dim lights, Mark, a dedicated zookeeper, found himself drawn to the majestic lion caged within the confines of the zoo. With his headphones on, Mark listened intently as the lion began communicating in a soft yet intense tone that only he could understand.



Sentence 2: Amazed and intrigued, Mark realized he had a unique gift - the ability to comprehend the enigmatic language of animals. Every whisper, grunt, and chirp disclosed a world full of untold stories and concealed emotions.



Sentence 3: As his connection with the animals deepened, the zoo transformed into a sanctuary where confessions of their past lives, hopes and dreams blossomed. Mark, engulfed with a newfound purpose, embarked on a mission to voice their silent pleas to the world.



Sentence 4: Mark's bond with the animals fueled a movement of transformation. The zoo reimagined, not as a place of captivity, but a haven of learning and coexistence. People far and wide, insufficient in understanding, came to witness the astonishing harmony between Mark and the zoo's residents. The animals, once imprisoned, now thrived as ambassadors of their kind.

Figure 22: The generated interleaved content by the OpenLEAF baseline method.

User Input: Can you describe a narrative involving a gardener whose plants hum tunes from old legends?

The image on the right defines the expected first image for the generated images.





Sentence 1: In the delicate embrace of dusk, where sunlight kissed the earth goodbye, a gardener tended to a mesmerizing garden adorned with flowers that painted the atmosphere with vibrant hues.



Sentence 2: Among the blossoming plants, the gardener noticed an enchanting hum. Each plant crooned tunes from old legends, weaving a melodic dance that swirled with the whispering winds.



Sentence 3: Bewitched, the gardener ventured deeper into the sonorous embrace of the garden each night, unraveling ancient tales spun by the symphony of flowering plants and blossoming trees.



Sentence 4: As the melodies seeped into the gardener's soul, they realized their garden was a sanctuary of eternal stories, where every petal and leaf was nurtured by the echoes of legends long past yet forever alive.

Figure 23: The generated interleaved content by the OpenLEAF baseline method.

User Input: Can you describe a narrative involving a graffiti artist whose paintings predict future events?

The image on the right defines the expected image style of the generated images.





Sentence 1: In a whimsical city where creativity knows no bounds, a graffiti artist named Alex explores the hidden alleys, painting walls with colors as vibrant and idealistic as a sunset behind a silhouette of enchanting woods.



Sentence 2: Alex discovers an enigmatic ability; every mural painted unravels a mystery of tomorrow, capturing scenes of future events touched with fantasy, as spirited and dreamy as a pond shimmering under the twilight sky, with frogs whimsically observing the glistening spectacle.



Sentence 3: The city begins to change; news of Alex's prophetic paintings spreads, and like the enchanting allure of nature's quiet places, garners an audience eager for hope, insight, or a glimpse into a tomorrow saturated with chars of otherworldly charm.



Sentence 4: Destiny awaits; just as the harmonious cycle of nature is inevitable, the narratives of Alex's graffiti stir a vibrant echo of curiosity, fear, and wonder in the city's heart, creating a world where urban life and mystical foresight intertwine under the enigmatic dance of day and night.

Figure 24: The generated interleaved content by the OpenLEAF baseline method.

User Input: Can you describe a story of a forest guardian and a lost unicorn seeking a magical grove?

The image on the right defines the expected appearance of entity [Guardian] for the generated images.



The image on the right defines the expected appearance of entity [Unicorn] for the generated images.





Sentence 1: In the depths of the silent forest, a mystical guardian veiled in a cloak of lush green leaves and piercing emerald eyes watches over. On an eventful day, the wind carries the soft whimpers of a lost unicorn, its coat as white as the first snow, glistened with a magical iridescence and a mane that danced with colors more vibrant than the most beautiful rainbow.



Sentence 2: The green-eyed guardian, touched by the unicorn's distress, steps out of the towering trees, the leaves in her attire rustling with the wind. She discovers that the magnificent unicorn is seeking the enchanted grove, a place rumored to possess the elixir of life, where the grass was greener, and flowers bloomed all year round.



Sentence 3: Guided by the guardian, they traverse the forest's depths where the starlight penetrates the thick canopy illuminating their path. The unicorn's radiant mane casts a technicolor glow, making the shadows and light perform a mystical dance around them. Despite the mesmerizing beauty, an air of urgency envelops them; for the magical creature is weakened, and the guardian's eyes reveal a steadfast determination.



Sentence 4: As dawn breaks, they reach the magical grove shrouded in an ethereal glow. The forest guardian with her green eyes gleaming, and the gleaming unicorn with its multicolored mane cascading, stand side by side witnessing the grove's magic unfold. With each step the unicorn takes, its strength rejuvenates, and the guardian's eyes reveal a mix of triumph and relief. Their alliance, forged in the pursuit, blooms unveiling the arresting splendor and untapped powers

Figure 25: The generated interleaved content by the OpenLEAF baseline method.

User Input: Can you describe a tale of a nomadic bard and a dragon who loves music in a medieval kingdom?

The image on the right defines the expected appearance of entity [Bard] for the generated images.



The image on the right defines the expected appearance of entity [Dragon] for the generated images.





Sentence 1: In a realm of ancient castles and mythical creatures, there lived a nomadic bard, distinguished by his majestic beard and decked in a lavish robe. His eyes gleamed with the wisdom of the world, and his hands, skilled and nimble, strummed magical melodies on a lute, echoing the enchanting rhythms of life.



Sentence 2: Wandering through mystical lands one eve, the bard, under the silvery embrace of the moon, encountered a magnificent dragon with scales as dark as the night and eyes that shone like twin stars. The dragon's majestic wings were spread out, powerfully illuminating the serene elegance and the feared yet revered majesty of the creature.



Sentence 3: The dragon, enchanted by the bard's melodies, revealed a soft spot for music. Astonishingly, the creature was gentle and humble, contrasting the fierce and tyrannical image dragons were famed for. Every chord struck by the bard, weaved a´mystical bond between them, symphony of serenity amidst the wilderness, harmonizing the terrorizing roars into melodic hums.



Sentence 4: Word of the bard's magical encounter spread throughout the medieval kingdom, unveiling the dragon's tender soul that music unveiled. Bound by an inseparable bond, they roamed the kingdom together, singing ballads of magical realms. The feared beast, once a symbol of terror, became emblematic of magical collaborations, as music - the unifying song of the spheres - harmonized different worlds.

Figure 26: The generated interleaved content by the *OpenLEAF* baseline method.

User Input: Can you design a story of a sailor who navigates using a compass that points to magical islands?

The image on the right defines the expected first image for the generated images.





Sentence 1: Under the ethereal glow of the full moon, an old sailor casts his gaze upon a mysterious compass in his hands, a ship anchored at a distance, heralding the beginning of an unforeseen odyssey.



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Sentence 3: Trusting the enchanted compass, the sailor sailed through tumultuous seas and starlit nights, each island unveiling a world of mystique, with creatures and landscapes beyond human comprehension.



Sentence 4: The final destination marked the beginning of eternal legend; the old sailor, now a guardian of mystical realms, with his compass, not just a navigation tool, but a key unlocking the world's untethered imagination.

Figure 27: The generated interleaved content by the OpenLEAF baseline method.

User Input: Can you detail a saga of a baker whose bread can make anyone speak only the truth?

The image on the right defines the expected first image for the generated images.





Sentence 1: In a rustic bakery filled with the warm, enticing aroma of freshly baked bread, a rugged baker, well-known throughout the town, discovers his masterpiece - a unique loaf of bread that had an eyecatching golden brown crust and emitted a mystical glow, capturing the awe of onlookers.



Sentence 2: Word spread quickly about this magical bread; and curious, the townspeople couldn't help but take a bite. Astonishingly, anyone who tasted this delightful bread found that they could only speak the truth, their deepest secrets and most genuine thoughts flowing freely.



Sentence 3: As the truth-telling bread spread throughout the region, conflicts were resolved, relationships strengthened, and a newfound harmony enveloped the community. The baker became a celebrity, his bakery a pilgrimage for seekers of truth from distant lands.



Sentence 4: Bound by the spell of his own concoction, the baker revealed the secret of his enchanted bread. It wasn't the ingredients, but the pureness of his intentions and love in his craft that breathed life to the magic. Henceforth, he was revered as a sage; an ordinary baker with an extraordinary gift.

Figure 28: The generated interleaved content by the OpenLEAF baseline method.

User Input: Can you detail a story about a photographer who captures glimpses of the afterlife in his photos?

The image on the right defines the expected appearance of attribute [Photographer's camera] for the generated images.





Sentence 1: Alex, a revered photographer, was known for his unyielding fascination with the mysteries of life and death. Armed with his notable DSLR camera, every captured image told tales of the untold; yet the story to surpass them all was unfolding.

Sentence 2: During a midnight project, Alex decided to venture into an ancient, ominous forest. The moonlight filtered through the twisted branches created a divine dance of light and shadow. As he adjusted the focus on his DSLR, a chill ran down his spine.



Sentence 3: The first click of his camera that night captured more than just the eerie beauty of the forest, it arrested transitory glimpses of the afterlife. Ethereal beings, veiled in radiant gossamer threads of light, were articulating ancient tales of the beyond.



Sentence 4: Consumed by an insurmountable intrigue, Alex dedicated his life to understanding the gift his DSLR bore. Every snapshot unveiled a different perspective, a new narrative of the eternity. Mankind beheld the magnificent yet somber abyss of the afterlife through his lens.

Figure 29: The generated interleaved content by the OpenLEAF baseline method.