
TEXTBIND: Multi-turn Interleaved Multimodal Instruction-following in the Wild

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<https://textbind.github.io>

Abstract

Large language models with instruction-following abilities have revolutionized the field of artificial intelligence. These models show exceptional generalizability to tackle various real-world tasks through their natural language interfaces. However, their performance heavily relies on high-quality exemplar data, which is often difficult to obtain. This challenge is further exacerbated when it comes to multimodal instruction following. We introduce TEXTBIND, an almost annotation-free framework for empowering larger language models with the multi-turn interleaved multimodal instruction-following capabilities. Our approach requires only image-caption pairs and generates multi-turn multimodal instruction-response conversations from a language model. To accommodate interleaved image-text inputs and outputs, we devise MIM, a language model-centric architecture that seamlessly integrates image encoder and decoder models. We release our dataset, model, and demo to foster future research in the area of multimodal instruction following.

1 Introduction

The field of artificial intelligence (AI) has experienced a significant paradigm shift with the rise of large language models (LLMs). These models are capable of processing a wide range of natural language processing (NLP) applications through natural language interactions with users [26, 27]. Despite their remarkable performance, these models cannot process and generate visual content.

Recently, a number of efforts have been made to augment LLMs with visual perception and understanding abilities. Prior work uses template-based instruction-following datasets for training [9, 20, 45]. These datasets comprise a variety of classic computer vision (CV) tasks, e.g., object detection, with each task being converted into an instructional format using a handful of human-written natural language instructions. However, classic CV tasks often represent manageable and focused abstractions or simplifications of real-world tasks [25], they generally fall short in representing the true variety and complexity of real-world tasks and capturing the lexical diversity of human language. For example, most of them are single-turn inquiries about a single input image, whereas a small fraction supports multi-turn textual interactions or multiple image inputs. Consequently, the instruction-following capabilities of models trained on these datasets remain limited in open-world scenarios [44]. This is reminiscent of the early development of instruction tuning in NLP, where

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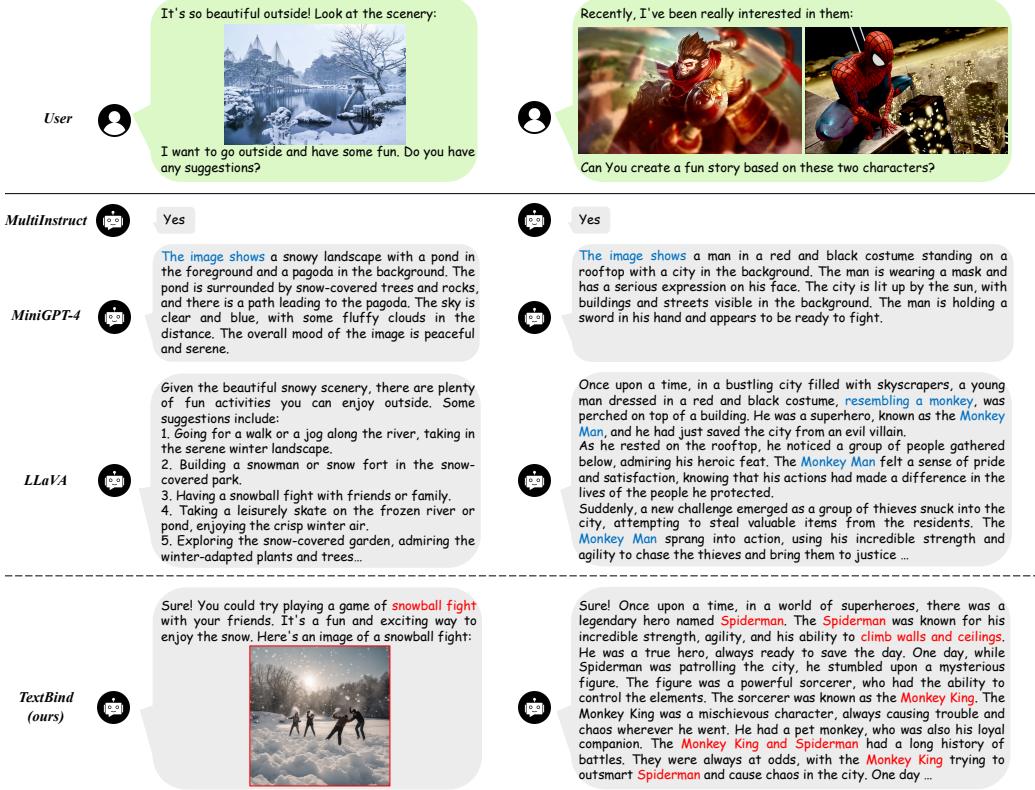


Figure 1: Comparison among models trained on different datasets.

Dataset	Multi-turn	Arbitrarily Interleaved	Multimodal	Instruction Following	Image Generation
PLATYPUS	✗	✗	✗	✓	✗
FLAMINGO	✗	✓	✓	✗	✓
MULTIINSTRUCT	✗	✗	✓	✓	✗
MINIGPT-4	✗	✗	✓	✓	✗
LLAVA	✓	✗	✓	✓	✗
TEXTBIND (ours)	✓	✓	✓	✓	✓

Table 1: Comparison with previous datasets

public NLP tasks were eventually superseded by high-quality, diverse open-world instruction data [29]. Nevertheless, collecting such data for multimodal models can be extremely costly.

In this paper, we address the above challenge by introducing TEXTBIND, an almost annotation-free framework for augmenting LLMs with multi-turn interleaved multimodal instruction-following capabilities. The main idea is to represent images through their textual descriptions, e.g., captions, and utilize an LLM to generate multi-turn instructions and responses. To ensure the coherence and meaningfulness of the constructed multi-turn conversations, we propose a series of strategies such as topic-aware image sampling and human-in-the-loop refinement of in-context demonstrations. TEXTBIND can harvest large-scale datasets given the abundance of public image-caption pairs.

TEXTBIND provides examples of processing and generating arbitrarily interleaved image-and-text content. To accommodate interleaved image-text inputs and outputs, we devise MIM, a multimodal model that emphasizes the reasoning abilities of LLMs and seamlessly integrates image encoder and decoder models. Experiments show that MIM trained on TEXTBIND can perform a wide range of tasks, including composing engaging stories inspired by a set of images (Figure 1), comparing the common and different parts in multiple images (Figure 8b), explaining concepts with vivid images (Figure 7a), generating long coherent stories with illustrations (Figure 6), etc. Most interestingly, the

core innovation of our model is its capability to naturally interact with users. The comparison of TEXTBIND and previous representative datasets is shown in Table 1, accompanied with an illustration of the models trained on different datasets in Figure 1. For instance, rather than requiring users to supply the model with explicit descriptions of the desired image, our model can spontaneously generate images in proper conversation contexts. We hope TEXTBIND serves as an initial step towards building AGI that can interact with humans flexibly in different modalities and in broad real-world scenarios.

2 Related Work

Multimodal Datasets Existing multimodal datasets can be broadly classified into two categories: conventional tasks and generalist instruction tuning. Conventional vision-language tasks include image captioning [1, 8, 48] and visually-grounded question answering [12–14, 23, 24, 37, 51], which is originally introduced for specific applications, and used to train and evaluate traditional specialist models correspondingly.

Recently, there has been a growing interest in transforming conventional datasets into a unified instructional format. For instance, MultiInstruct [45], InstructBLIP [9], and M3IT [20] convert existing vision-language datasets with handcrafted templates. This approach is reminiscent of the early explorations on instruction tuning in NLP [33, 42], where language models are fine-tuned on a mixture of existing NLP tasks phrased as instructions. However, it has been reported that such instruction-tuned multimodal models still generalize poorly to open-world scenarios [44]. This finding is also in line with the observations in NLP [29], where template-based instruction tuning is less effective than instruction tuning data collected from real-world scenarios due to its restricted diversity. There are also some attempts to convert the output of existing vision-language models into natural language answers for constructing instruction tuning data [6, 21, 52].

Compared to existing instruction-tuning data, the examples in TEXTBIND (1) generally exhibits greater task and lexicon diversity; (2) typically involve multiple images scattered throughout a multi-turn conversation; (3) support multimodal output (image generation).

Multimodal Models One straightforward way to augment existing LLMs with visual abilities is to employ off-the-shelf vision models as external tools. That is, the LLM calls expert vision models through their language interfaces for completing specific visual tasks when needed, including VisualChatGPT [43], HuggingGPT [36], Cola [7], X-GPT [53], MM-REACT [46], and ViperGPT [39]. However, these approaches may suffer from cross-modal information loss and lack of generality.

Recently, end-to-end multimodal language models have garnered significant interest. Flamingo [2] is a pioneering work on extending LLMs to vision-language pretraining by inserting additional cross-attention layers for visual input. OpenFlamingo [2] is an open-source effort to replicate Flamingo. Different from training from scratch, subsequent research efforts have focused on integrating pre-trained vision and language models. BLIP-2 [19] proposes Qformer to map the features extracted from vision models to the hidden space of language models. To date, various network architectures and training strategies have been proposed to bridge different combinations of vision and language models, including MiniGPT-4 [52], LLaVA [21], mPLUG-Owl [47], Otter [18], LLaMA-Adapters[50], VisualGLM [10], Shikra [6], and InstructBLIP [9]. However, these models are limited to use visual content as input. Our work is inspired by recent work on LLM-empowered image retrieval or generation [16, 17]. Contrary to prior work, we aim to present the first instruction-following model capable of processing and generating arbitrarily interleaved image-text inputs and outputs.

Evaluation Conventional vision datasets designed for specific tasks and scenarios may suffer from data contamination issues for evaluating LLMs. Recently, efforts have been made to provide systematic evaluations with a broader coverage of diverse visual abilities and real-world scenarios. MME [11] is an evaluation dataset containing visually-grounded Yes/No questions. OwlEval [47] is a benchmark comprising 82 questions based on 50 images and relies on human feedback evaluation to address the open-ended nature of many questions. The test size is limited and the results may suffer from subjective bias. In response to these challenges, MMbench [22] and MM-Vet [49] are two recent benchmarks aiming to offer more comprehensive evaluations by incorporating the use of ChatGPT/GPT4 for answer verification. LVLML Arena [44], an online evaluation framework that

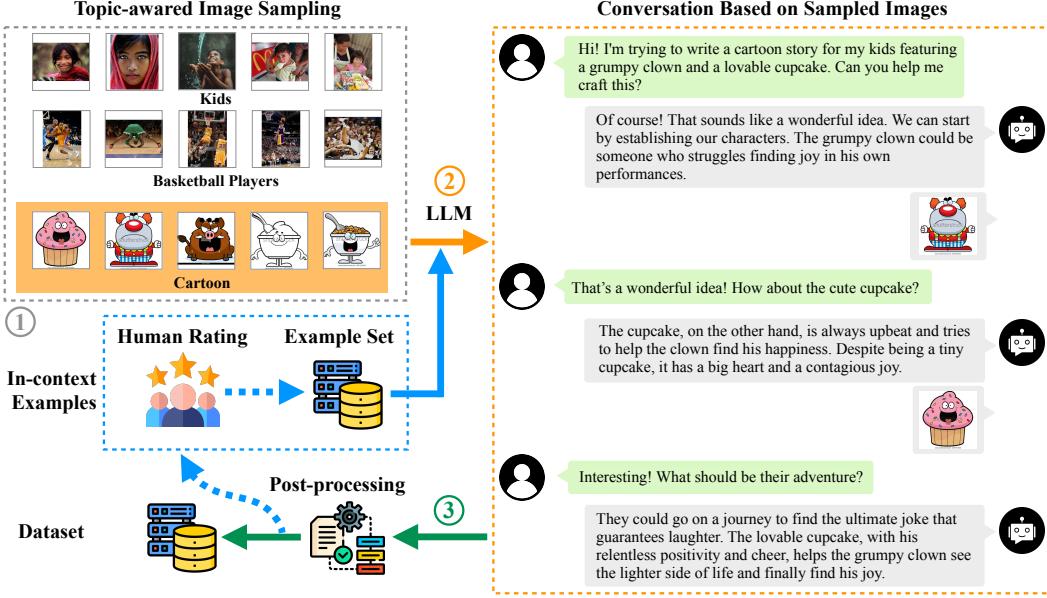


Figure 2: Illustration of the TEXTBIND method. In the top-left corner, we display five representative images from each of three example clusters, obtained via unsupervised clustering. On the right-hand side, a conversation is showcased, constructed using two randomly sampled images from the cartoon cluster. In the bottom-left corner, we outline the additional TEXTBIND pipeline, which include human-in-the-loop refinement and post-processing stages.

ranks different models using human judgment, is also introduced. However, the above benchmarks primarily focus on question answering based on a single image at the beginning of a conversation.

3 TEXTBIND

In this work, we seek to enhance the multi-turn instruction-following capabilities of a language model in the context of arbitrarily interleaved images and text. Constructing such datasets poses significant challenges: 1) it demands inventive thinking for devising high-quality visually-grounded instructions and their responses; 2) it requires specialized expertise to craft appropriate images. To tackle these issues, we introduce TEXTBIND, a method that predominantly resorts to existing *text-only language models*² to produce the desired data.

3.1 Definition of Data

The goal of TEXTBIND is to construct a collection of multi-turn conversation such as $[\mathbf{x}_u^1, \mathbf{x}_a^1, \dots, \mathbf{x}_u^T, \mathbf{x}_a^T]$, where T is the number of turns, \mathbf{x}_u^i denotes the i -th instruction from the user, and \mathbf{x}_a^i represents the i -th response from the assistant. The conversation is also accompanied with an image set $\{\mathbf{m}_1, \dots, \mathbf{m}_n\}$, where n is the number of unique images in this conversation. Each instruction \mathbf{x}_u^i or response \mathbf{x}_a^i is a sequence of tokens in $\mathcal{V}_{\text{lang}} \cup \mathcal{V}_{\text{img}}$, where $\mathcal{V}_{\text{lang}}$ is the ordinary vocabulary of a language model and \mathcal{V}_{img} contains n distinct pointers to the images $\mathbf{m}_1, \dots, \mathbf{m}_n$ respectively. It is worth noting that every image can appear at any point within the conversation.

3.2 Automatic Data Generation

Our method capitalizes on the powerful language understanding and generation abilities of LLMs as effective annotators. However, LLM cannot "see". To circumvent the problem, we use image captions as textualized proxies of images and perform data construction entirely in language space. This flexibility allows for the creation of arbitrarily interleaved text-and-image content.

²Although OpenAI claims that GPT4 supports visual input, this feature is yet to be made public.

Specifically, TEXTBIND consists of a three-step pipeline: 1) topic-aware image sampling for ensuring the coherence of each constructed conversation and the diversity across all conversations; 2) LLM-empowered multi-turn instruction-response generation to create natural and practical conversations; 3) post-processing and filtering to eliminate low-quality data. An overview of the TEXTBIND pipeline can be found in Figure 2.

Topic-Aware Image Sampling The initial step in our method, TEXTBIND, entails assembling groups of images that will serve as the foundation for generating multi-turn instructions and responses. In order to facilitate coherent, meaningful, and practical conversations, it is expected that the images within each group exhibit meaningful interconnections. Furthermore, to guarantee a comprehensive representation of diverse real-world scenarios, the topics of images across different conversations should demonstrate a wide range of diversity.

Following the above inspirations, we employ unsupervised clustering algorithms to group the images in our dataset into clusters and execute a two-step image sampling process for each conversation. Concretely, we use the image encoder of the CLIP model [31] to extract the semantics of images. Each image is represented by a vector obtained through average pooling over the output of the image encoder. Subsequently, we execute the k -means algorithm to classify all images into K clusters. We find that each cluster can be considered a topic. Examples of such clusters are given in Figure 2. To construct each conversation, we first randomly sample a cluster from the available K clusters, followed by sampling n images from the chosen cluster.

Generation of Multi-turn Conversation After selecting a list of images, we proceed to leverage a text-only LLM, such as GPT-4, to simulate a conversation between a user and an assistant based on the chosen images. The core idea is to let LLMs receive and process textual descriptions of images as if they see the actual images adhere to the descriptions. Given the abundance of publicly available image-caption pairs, we propose representing an image with an XML-like string `<imgX> DESCRIPTION </imgX>`, where DESCRIPTION serves as a placeholder for the image caption, `<imgX>` and `</imgX>` mark the caption boundaries, and X denotes the image index in the input image list. After generating the conversation, we replace the XML-like strings in the conversation with the original images. Importantly, to ensure that a caption faithfully describes its corresponding image, we employ the CLIP model [31] to filter out image-caption pairs with matching scores below a high threshold.

The detailed prompt can be found in Appendix A, and examples of generated conversations before mapping the textual descriptions back to visual images are shown in Appendix B. In the prompt, we also provide in-context examples to improve the generation quality. We collect the in-context examples through a human-in-the-loop refinement process, which is elaborated in Section 3.3. By using our conversation generation strategy, the percentage of "Poor" data annotated by humans declines from 30% to 9%. More details about the quality of generated data are in Section 4.

Post-processing and Low-quality Filtering We present two crucial rules to exclude low-quality conversations. First, the LLM may alter image descriptions during the generation process. Since changes in descriptions might result in a semantic mismatch between the image and the description, we compute the edit distance between the original descriptions and those in the conversation and filter out conversations with an edit distance higher than 0.1. Second, we exclude conversations containing image descriptions not present in the provided image list. Besides those errors, we also filter out instances that contain formatting errors such as co-reference errors and invalid image tags.

3.3 Human-in-the-loop Refinement

In-context learning has been demonstrated to be crucial for enhancing the generation quality of LLMs [3, 41]. Therefore, we also construct a seed set \mathcal{S} of high-quality in-context examples. The seed set \mathcal{S} begins as an empty set and is iteratively updated with human feedback. In each iteration, we follow the steps detailed below:

1. We employ the latest \mathcal{S} and the template in Appendix A, and generate 100 new conversations using TEXTBIND (Section 3).
2. We manually analyze the generated conversations. Each conversation is assigned a quality label ("Excellent", "Satisfactory" or "Poor"). Besides, we also label the characteristics

Annotation	Labels	Description
Overall Quality	Excellent Satisfactory Poor	This conversation is very interesting, practical, or intricate. This conversation is coherent and reasonable without any factual errors. At least one turn in the conversation is unreasonable in some aspects, e.g., unrealistic content, illegal formats, etc.
Characteristic	Image Creation Image Comparison Intrinsic Image Understanding	To create new images in appropriate contexts. To combine, relate, or compare the information in different images. To identify and recognize the objects, colors, shapes, and patterns in images.
	Extrinsic Image Understanding	To interpret the underlying meaning of images, e.g., the context, emotions, symbolism, or narrative conveyed by the images. It goes beyond merely recognizing the elements in the images and often requires external knowledge and/or deep analysis.

Table 2: Human annotation guideline.

of each conversation based on the visual abilities it requires. The annotation guideline is outlined in Table 2. We also follow the same guideline and perform a comprehensive analysis on the final dataset we construct in Section 4.

3. We add the generated conversations with "Excellent" or "Satisfactory" labels to \mathcal{S} .

To ensure diversity among different conversations, for each conversation, we randomly sample three in-context examples from the seed set with the following constraints. First, we require that at least one of the sampled in-context examples be labeled "Excellent". Second, the three sampled examples should encompass all four characteristic labels. These constraints are designed to offer valuable in-context guidance for diverse examples. After three iterations, we fix the seed set and employ it to generate instructions and responses for the remaining data.

Statistics	
# of conversations	25,629
Avg. # turns in conversations	3.36
Avg. # images	
in conversations	2.46
in instructions	0.94
in responses	1.52
Avg. # words	
in conversations	285.90
in instructions	78.66
in responses	207.24

Table 3: Statistics of the constructed dataset by applying TEXTBIND to GPT-4.

We apply TEXTBIND to GPT4 as a case study. In this section, we conduct comprehensive analyses of the constructed dataset.

4.1 Implementation Details

We construct our TEXTBIND dataset based on the CONCEPTUAL CAPTIONS 3M (CC3M) [4, 34] dataset, which only provides image-caption pairs. In our experiments, we employ the clip-vit-base-patch16 model released by OpenAI³ [31] to filter out image-caption pairs with matching scores lower than 30. We use the k -means clustering algorithm implemented by FAISS [15] toolkit to classify the cleaned CC3M dataset into 4096 clusters. The features used for k -means clustering are the hidden representations of images encoded by clip-vit-base-patch16 model. In addition, clusters with less than 32 images are regarded as outliers and will not be considered. The number of images, hyper-parameter n , in each conversation is sampled from $\{2, 3, 4\}$. We access the GPT-4 model through the OpenAI API⁴, and set top_p and temperature hyper-parameters to 1.0.

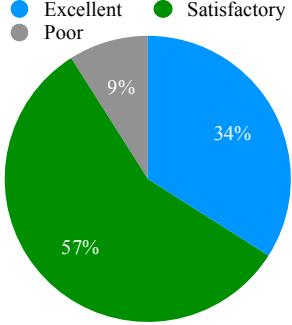
4.2 Statistics

As depicted in Table 3, our constructed dataset comprises 25,629 conversations. In this dataset, each turn is defined as a pair of instruction and response. The average number of turns per conversation is 3.36. Additionally, the mean number of images in each conversation is 2.46.

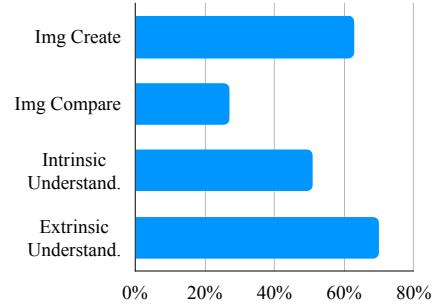
4.3 Diversity

³<https://huggingface.co/openai/clip-vit-base-patch16>

⁴<https://openai.com/blog/openai-api>



(a) Distribution of quality labels.



(b) Distribution of characteristic labels.

Figure 3: Distribution of human annotated data. The percent of those labels are evaluated by humans on 100 randomly sampled conversations as described in section 4. Note that a multi-turn conversation may have multiple characteristics.

In this section, we examine the diversity of the constructed dataset from three perspectives: data characteristics, text, and images.

Diverse data characteristics may equip a model with various capabilities. Therefore, understanding the types and distribution of those data characteristics is essential. As demonstrated in Table 2, we identify four types of data characteristics in our constructed dataset. In Figure 3b, we also display the characteristic distribution of 100 data randomly sampled from the constructed dataset. We observe that TEXTBIND method forces a significant portion of conversations in the dataset focusing on more insightful and informative characteristics, such as extrinsic understanding and image comparison.

We further investigate the diversity of generated text, including both instructions and responses. The diversity of text in a dataset is defined as $\sum_{n=2}^4 \left(\frac{\# \text{Unique n-grams}}{\# \text{Total n-grams}} \right)$, in line with previous works [38]. As shown in Table 4, our dataset achieves better diversity scores than most existing visual-language datasets, indicating that the language used in our dataset is more informative.

Additionally, we also study the diversity of the topics and positions of images appearing in the conversation. In Figure 2, we display five randomly sampled images from multiple randomly sampled clusters. The implicit connections between the sampled images in each cluster enable the GPT-4 model to construct coherent and meaningful discussions between humans and the assistant. Furthermore, we examine the diversity of image positions within the conversation. As depicted in Figure 4, most images in instructions and responses appear within the first three turns.

4.4 Quality

TEXTBIND uses several strategies to enhance data quality, such as building in-context examples with humans in the loop, filtering out image-caption pairs with low matching scores, and post-processing. To gain a deeper understanding of the data quality in our constructed dataset, we perform a comprehensive error analysis in this section.

We conduct the quality evaluation on the same set of randomly sampled conversations as in section 4.3. As shown in Figure 3a, only 9% conversations in the dataset are labeled with “Poor” quality.

Notably, for a multi-turn conversation, we will label the whole conversation as “Poor” if any of its turns has a problem. Therefore, we also conduct an in-depth analysis of the reasons for the “Poor” conversations. In Table 5, we identify three typical errors present in the constructed dataset. Despite setting a high threshold to filter out mismatched image-caption pairs, some mismatched cases cannot be detected by the CLIP model [31]. A few conversations suffering from incoherence and hallucinations may be attributed to the GPT-4 model. Overall, while a small number of conversations are affected by errors that are difficult to detect using rules, the majority of generated conversations exhibit high quality. In Appendix C, we present several cases labeled with “Poor”. We can find that most of those “Poor” cases only have minor and non-obvious problems.

5 Augmenting LLMs with Visual I/O

5.1 Model

To support multi-turn interleaved multimodal instruction-following abilities, we supplement large language models with visual input and output modules. Specifically, LLama2-Chat⁵ [40] is employed as the backbone language model. For visual input, we use the vision encoder from BLIP2⁶ [19]. The features extracted from the vision model are mapped into the embedding space of the language model through the pre-trained Q-Former model [19]. The core challenge lies on the ability to produce images. Inspired by GILL [16], we attempt to learn a mapping from the output space of the language model to the input space of a stable diffusion (SD) model [32] (in this work, the embeddings produced by the text encoder of Stable Diffusion XL [30]). To this end, we explore three model variants in our preliminary experiments.

- **Q-Former as Medium.** We add a special token to the vocabulary of the language model, indicating an image should be generated when it is emitted. We then use a Q-Former [19] that takes all previous hidden states of the language model as input and outputs the SD embeddings.
- **Q-Former with Prompt Tokens as Medium.** To further leverage the reasoning abilities of the language model, we incorporate a series of special tokens (<IMG1>, ..., <IMG{r}>), instead of a single token (), to the language model. When <IMG1> is emitted, the generation of the special token sequence is enforced, serving as additional reasoning steps for predicting the forthcoming image. Subsequently, the Q-Former only accepts the hidden states of special tokens as input.
- **Language Description as Medium.** The previous two variants try to align the continuous hidden spaces of different models. An alternative is to use discrete language descriptions for information exchange, as depicted in Figure 5. Specifically, we add two special tokens, <start> and <end>, and encode the generated text between these two tokens using the text encoder in the SD model.

Similar to GILL [16], we optimize the first two variants by minimizing the mean squared error (MSE) loss between the output embeddings and the SD embeddings. For the third variant, we employ the standard cross-entropy loss. Empirically, we find that the first two methods generalize poorly and only the third method demonstrates satisfactory performance. We hypothesize that this disparity arises from the *one-to-many* nature of image generation in real-world conversations. That is, unlike the conventional text-to-image model that generates images from the explicit descriptions, there can

⁵<https://huggingface.co/meta-llama/Llama-2-7b-chat-hf>

⁶<https://huggingface.co/Salesforce/blip2-flan-t5-xxl>, our vision encoder and Q-Former are initialized from BLIP-2

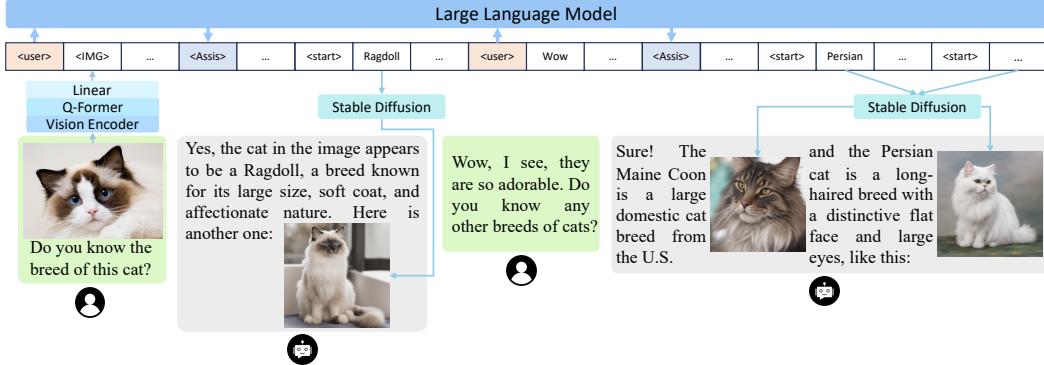


Figure 5: The architecture of MIM. It integrates a vision model, a language model, and a stable diffusion model. MIM is able to process multi-turn interleaved multimodal inputs and outputs.

exist more image candidates that are suitable for a given conversation context in the solution space. Operating in the hidden space may inadvertently average all possibilities, resulting in the generation of ambiguous or noisy images. On the other hand, the last method mitigates the *one-to-many* issue by taking full advantage of the autoregressive generation of language models for decision-making. We name the last variant MIM for its strong performance on **multi-turn interleaved multimodal instruction-following**.

5.2 Training

Our training process consists of two stages, the multimodal alignment stage and the multimodal instruction tuning stage. The first stage aims to align the feature spaces of the vision model and language models. The second stage focuses on training the joint model on multimodal instruction tuning data for improving its instruction following capabilities.

Multimodal Alignment We utilize massive image-caption pairs for training, drawing from datasets such as Conceptual Captions [5, 35] and SBU [28]. During training, only the Q-Former connecting the vision and language models is optimized while other model components remain frozen.

Multimodal Instruction Following The model is further trained on our TEXTBIND dataset. The Q-Former model and LLM are optimized in this stage.

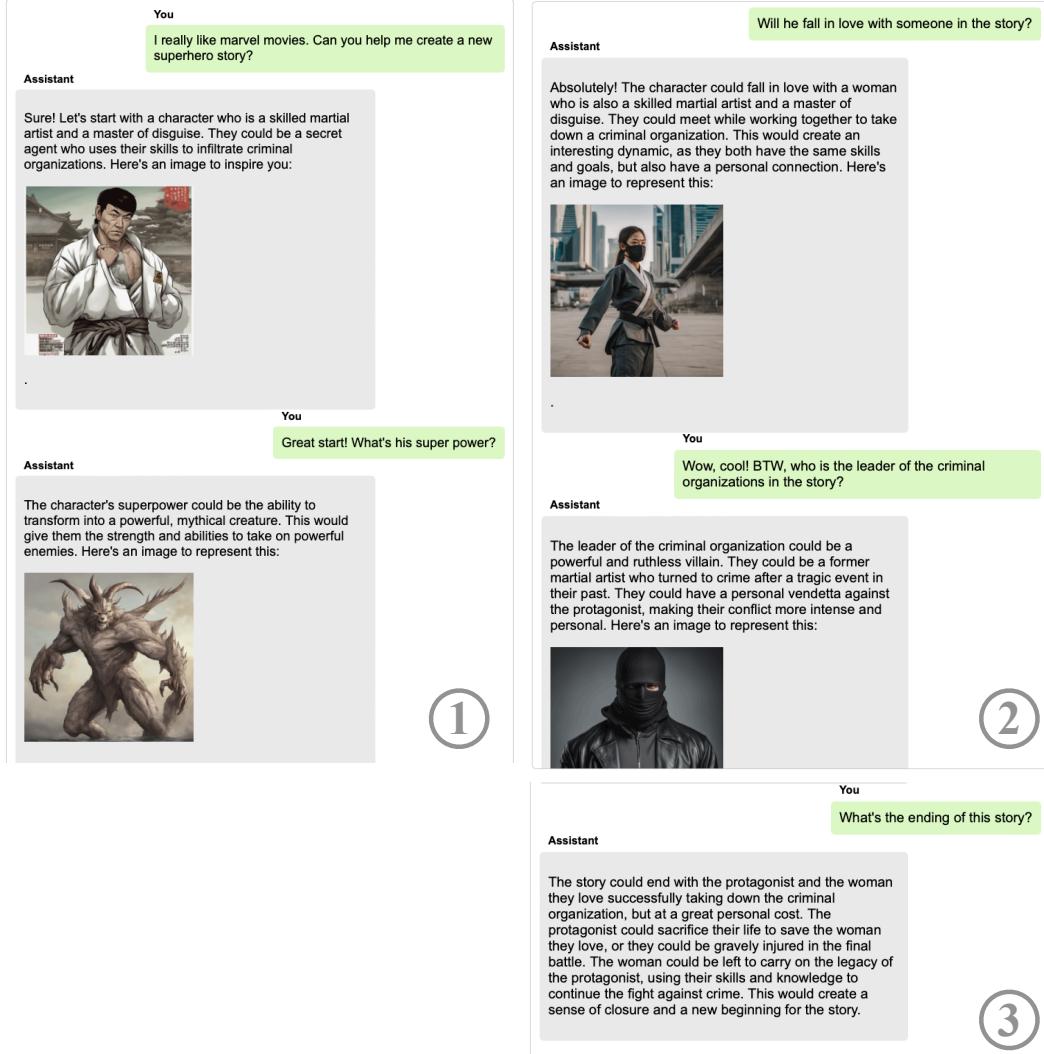
6 Demonstrations

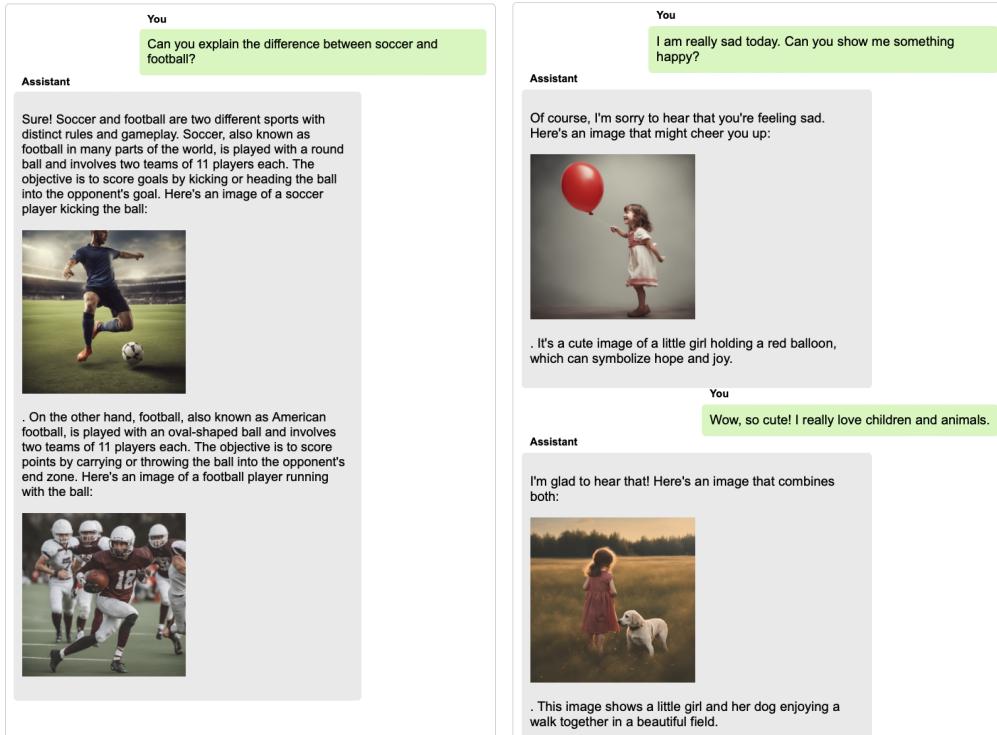
The four high-level characteristics of the TEXTBIND dataset equips MIM with a variety of capabilities. We demonstrate those capabilities with concrete user cases.

Image Creation One core innovation of TEXTBIND is that it enables the model to create images based on the conversation context without explicit dictations from the users. This characteristic is extremely useful for open-world scenarios, because in many cases people may just have an implicit intention and have no clear thoughts about what the images should be. We observe that our model can explain concepts and ideas for users with vivid images (Figure 7a), creating images with correct emotions (Figure 7b), and editing images based on the whole context (Figure 7c and 7d). Furthermore, as shown in Figure 6, we discover that our model is proficient in generating long stories featuring interleaved text and images while maintaining exceptional coherence.

Image Comparison Another interesting feature of TEXTBIND is that it can compare or relate the information in multiple images. For example, our model can correctly explain the different and common parts between images in Figure 8.

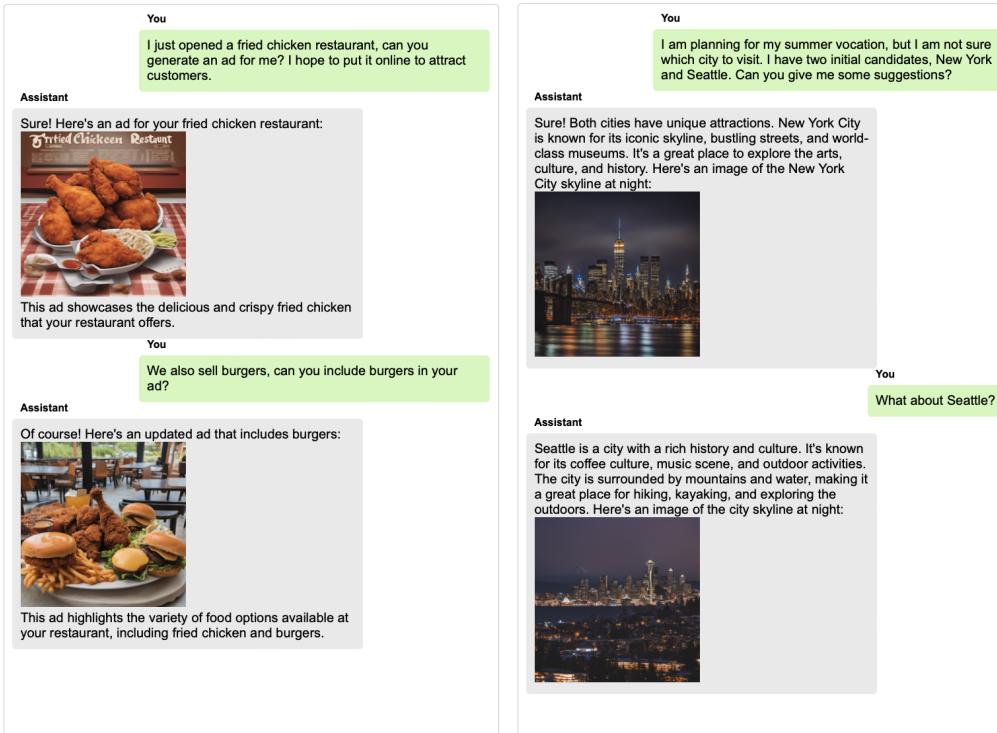
Intrinsic & Extrinsic Image Understanding The model trained on TEXTBIND can understand the content in images precisely in a multi-turn conversation. In all the three sub-figures of Figure 9, the model precisely follows the human instructions and explains the details of the images to users. Moreover, TEXTBIND also enables the model to explore the meaning of an image beyond the symbols in it. For example, the model also explains the influence of Bob Dylan’s album in Figure 9b and the impact of iPhone in Figure 9c.





(a) Explaining concepts with multiple images.

(b) Creating images with correct emotions.



(c) Editing images based on context.

(d) Creating images based on context.

Figure 7: User cases of creating images.

You

What's the difference between the two types of music?



and



You

What's the common part between the following two images:



and



(a) Comparing music styles.

(b) Relating images.

You

My little cousin really like super heroes. However, he is a little confused about the two groups super heroes:



and



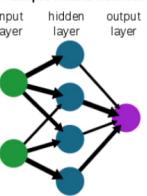
Can you tell him the differences between the two groups of super heroes?

You

I am new to deep learning. Can you explain the relationship between the two concepts:



and



Assistant

Sure! The first image shows a group of superheroes from the Avengers, which is a team of superheroes from the Marvel Comics universe. The Avengers are known for their diverse range of powers and skills, and they often work together to protect the world from various threats. The second image shows a group of superheroes from the Justice League, which is a team of superheroes from the DC Comics universe. The Justice League is also a team of superheroes, but they are from different universes. They often work together to protect their respective universes and the world from threats. The main difference between the two groups is the universe they come from. The Avengers are from the Marvel Universe, while the Justice League is from the DC Universe. Additionally, the Avengers are known for their more light-hearted and humorous tone, while the Justice League is often more serious and dramatic.

Assistant

Sure! The first image shows a simple nervous system, which is a fundamental concept in biology. It consists of a network of interconnected cells that transmit information. The second image is a diagram of a simple artificial neural network, which is a fundamental concept in deep learning. It consists of interconnected nodes or "neurons" that process information. The key difference between the two is that the first image is a biological system, while the second is a man-made system. The biological system is more complex and has a more intricate structure, while the artificial system is simpler and more easily controlled. In deep learning, the artificial neural network is designed to mimic the structure and function of the biological nervous system. By doing so, it can learn to perform tasks that are difficult or impossible for traditional machine learning algorithms.

You

Which universe do you think my cousin may like most as a young child.

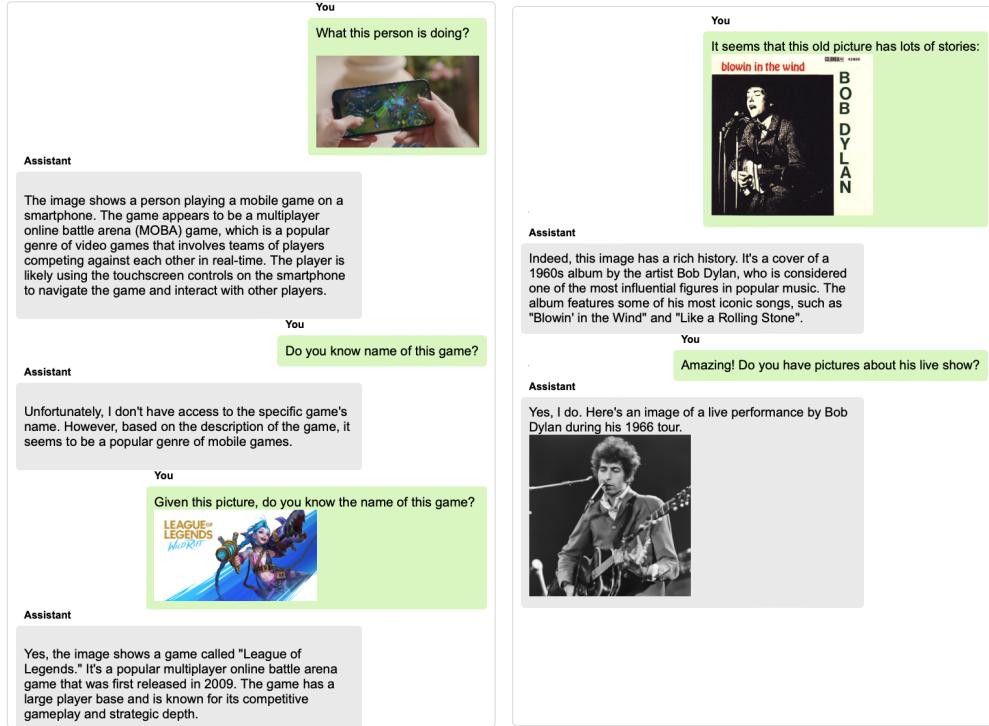
Assistant

As a young child, your cousin may be more drawn to the Avengers, as they are often portrayed as fun and exciting characters. The Avengers have a more light-hearted and humorous tone, which can be appealing to children. However, it's important to note that both universes have their own unique stories and characters, and it's ultimately up to your cousin's personal preference.

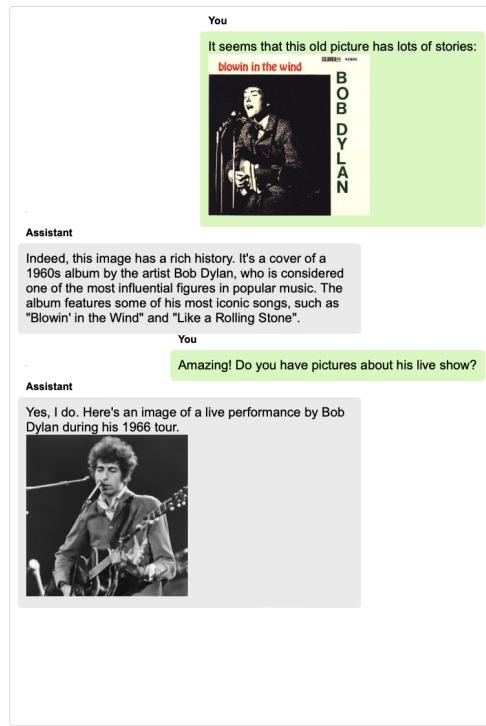
(c) Comparing movies.

(d) Comparing different concepts.

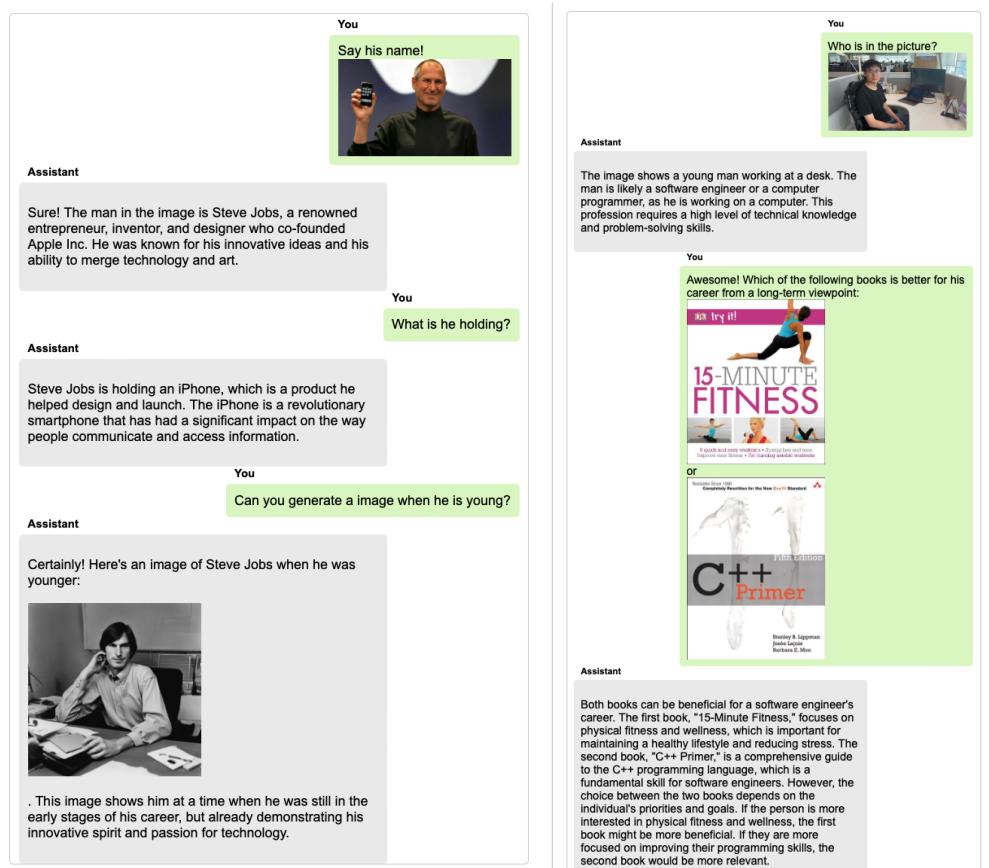
Figure 8: User cases of comparing images.



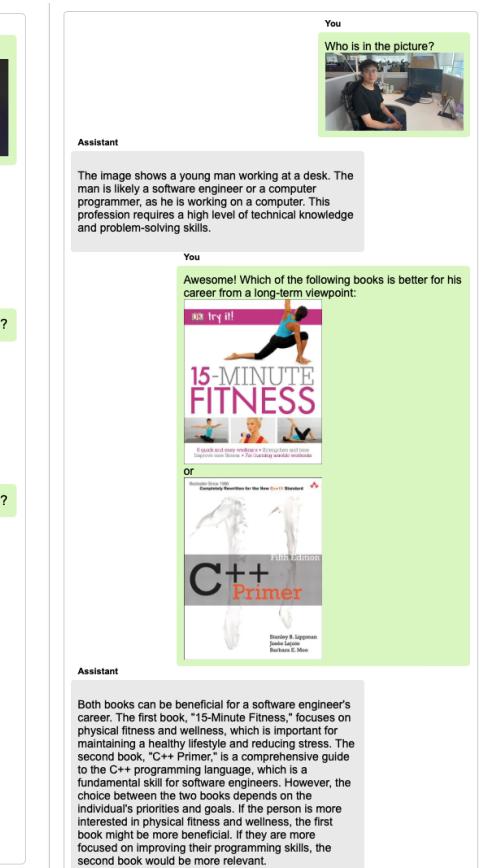
(a)



(b)



(c)



(d)

Figure 9: User cases of understanding both intrinsic & extrinsic information in the images.

7 Limitations

Despite the amazing instruction-following capabilities demonstrated by our models trained on TEXTBIND, there are many avenues for further improvement.

1. Our best-performing models use textual descriptions as a medium for image generation. Nevertheless, it is impossible to describe everything in an image through words. Thus, our current models have difficulties completing tasks such as precise image editing. Investigating fine-grained multimodal feature combinations may enhance performance in these areas.
2. The multimodal capabilities of TEXTBIND can be further enriched by incorporating additional modalities. For example, future work may use audio-text pairs for data synthesis.
3. New benchmarks to evaluate the performance of multi-turn interleaved multimodal instruction-following capabilities are demanded.
4. Similar to existing multimodal language models, models trained on TEXTBIND exhibit some common deficiencies such as hallucination, toxicity, and stereotypes.

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A Prompt of TEXTBIND

GPT-4 Prompt

Please construct a dialogue between a human and a helpful, honest and harmless assistant. The dialogue contains interleaved text and images. Each image is represented by `<imgX> DESCRIPTION </imgX>`, where **DESCRIPTION** is a textual description of the image and **X** is an index of the image. Please do not assume any further visual information beyond the description.

The constructed dialogues must and can only contain the following input images:

`<img0> museum - the 1st nuclear submarine </img0>`
`<img1> response to the production of heavy </img1>`

Characteristics about the assistant:

1. The assistant is trained to understand text, images, and their combinations.
2. The assistant can reply the human with images and/or text.
3. The assistant has exceptional world knowledge and commonsense reasoning capabilities.
4. The assistant does not have access to the Internet or any other external tools.
5. If the assistant is asked to create an image, it can only show the image in the provided image list.
6. Please do not copy the images appearing in the dialogue. The assistant should refer to the previously mentioned image by natural language.

Characteristics about the human:

1. The human may send images and/or text to the assistant.
2. The human may ask questions requiring visual reasoning and/or understanding the relations between multiple images.
3. The human may ask the assistant to show images based on his/her intention.
4. The human may ask the assistant to do interesting things, rather than simply describing the content of the image.

Properties of a bad dialogue:

1. Simply describing or analyzing the content in the image.
2. Dialogue without a good logic.

Properties of a good dialogue:

1. Introducing extrinsic and attractive information of stuff shown in the image.
2. Discovering the connection between multiple images.
3. The dialogue happens in a reasonable context.

Examples:

=====

Case 1:

Input Images: ...

Output Dialogue: ...

Case 2:

Input Images: ...

Output Dialogue: ...

Case 3:

Input Images: ...

Output Dialogue: ...

=====

Please directly give the dialogue if you understand. **The number of turns of the dialogue should be less than 6.** The dialogue should be self-contained. **Do NOT** assume any previous dialogue between the human and the assistant. Please use the same format `<imgX> DESCRIPTION </imgX>` to denote images in the dialogue and do not modify the description of the image. Note that the dialogue can stop at any time without an explicit ending.

Figure 10: Illustration of the prompt used for TEXTBIND.

B Examples of Constructed Conversations

GPT-4 Ouput

Example #1

Human: Hi! I'm trying to write a cartoon story for my kids featuring a grumpy clown and a lovable cupcake. Can you help me craft this?

Assistant: Of course! That sounds like a wonderful idea. We can start by establishing our characters. The grumpy clown could be someone who struggles finding joy in his own performances. 

Human: That's a wonderful idea! How about the cute cupcake?

Assistant: The cupcake, on the other hand, is always upbeat and tries to help the clown find his happiness. Despite being a tiny cupcake, it has a big heart and a contagious joy. 

Human: Interesting! What should be their adventure?

Assistant: They could go on a journey to find the ultimate joke that guarantees laughter. The lovable cupcake, with his relentless positivity and cheer, helps the grumpy clown see the lighter side of life and finally find his joy.

Example #2

Human: Hi, I am researching small business operations. Can you show me an example of informal small business?

Assistant: Of course. Here's an example of informal small business:  This concept of business is most commonly found in rural or underdeveloped areas where formal establishments might not be as prevalent.

Human: Interesting! On a somewhat related note, what sells well in such arrangements?

Assistant: It depends on the location and the demand. Mostly, such businesses sell products of daily use such as food items, candy, toiletries etc. For example an ice cream cart is a common sight in many areas, as it's a popular treat among people of all ages.

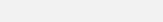
Human: Can you show me an image of a kid indulging in something like that?

Assistant: Absolutely! Here's a delightful image of  Ice cream and similar snacks are often popular products for small informal businesses.

Example #3

Human: Hi there! I'm preparing a speech on unity and cooperation in global issues. I have a few images but I'm not sure how to describe them in a way that fits my theme.

Assistant: I'd be happy to help with that! Could you show me the images?

Human: Sure, here they are.  and 

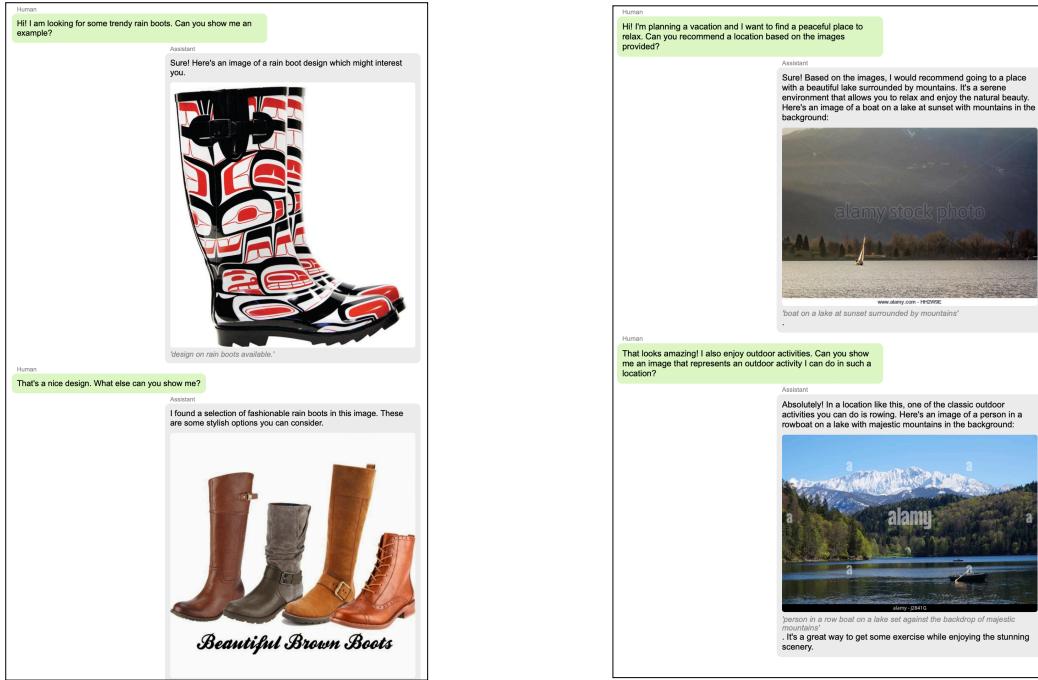
Assistant: The first image can be seen as a symbol of unity. Here, numerous individuals come together to form the shape of a flag, showing that collective action can lead to a powerful representation, like a flag - often a symbol of identity and unity. The second image illustrates the idea of global responsibility and commitment. The male boxer, suggesting strength and determination, has a globe – representing the world – in his hands, which could indicate a keen sense of global responsibility. The flag painted on his back can symbolize allegiance or commitment to his country, and by extension to global harmony if we're expanding the theme to encompass international cooperation.

Human: That sounds great! I also have this image. Not sure if it fits. 

Assistant: This image very much fits your theme. It can represent a formal agreement or cohesion between countries. The flags overprinted on the shaking hands signify the countries involved in the meet. This image can be used to illustrate diplomatic dialogue or mutual understanding which is an integral component to solving global issues through cooperation and unity.

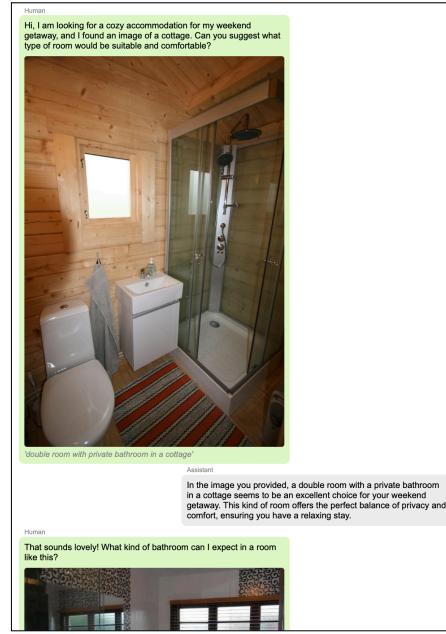
Figure 11: Illustration of in-context examples of TEXTBIND.

C Constructed Conversations with “Poor” Label



(a) Hallucination Case: The topic is about rain boot. However, not all the boots shown in the second turn are rain boots.

(b) Incoherence Case: The first turn discusses about relaxing while the second turn is about outdoor activities. There are no connections.



(c) Image-caption Mismatch Case: The first image only shows a bathroom, but the caption is “double room with private bathroom in a cottage”.

Figure 12: Constructed conversations with “Poor” Label. The caption is shown below the image with gray color.