Understanding Multimodal Instruction Format for In-context Learning

Anonymous Authors[1]

Abstract

The field of vision and language machine learning has witnessed a surge in interest regarding in-context learning—a technique that enables rapid adaptation to new tasks with just a handful of annotated examples. To improve the in-context learning capabilities of multimodal large language models (MLLMs), researchers have explored various instruction tuning formats. In this paper, we dive deeper into the instruction paradigm design to further enhance the in-context learning ability of MLLMs. We propose **U**nified **M**ultimodal **I**nstruction **T**uning (`UMIT`), a framework for constructing a text-image interleaved instruction dataset by merging diverse visual instruction datasets into a unified multimodal instruction format. To examine the effectiveness of `UMIT`, we train several models based on OpenFlamingo in different multimodal instruction formats used by existing MLLMs. Extensive experiments confirm that `UMIT` can significantly improve the in-context learning ability on a wide range of vision-language tasks, compared with prior formats, including MME Benchmark and SEED-Bench. Furthermore, we conduct a comprehensive study on the impact of different components in multimodal instruction formats on in-context learning in 3 classic vision-language tasks. The results indicate that `UMIT` successfully helps the model focus on task-specific information within effective in-context demonstrations, thus giving it remarkable advantages over prior formats on zero- and few-shot generalization during both training and testing stages.

1. introduction

GPT-4 (OpenAI, 2023) exhibits astounding performance in many vision-language tasks. One charming property of GPT-4 is its' in-context learning ability, which enables rapid adaption to new tasks with just a handful of examples. Although there have been many Multimodal Large Language Models (MLLMs) proposed (Liu et al., 2023b; Zhu et al., 2023; Huang et al., 2023; Dai et al., 2023), their primarily focus is to improve models' zero-shot performance, leaving the way of enhancing in-context learning less explored.

Furthermore, in the research line of multimodal in-context learning, Flamingo (Alayrac et al., 2022) and OpenFlamingo (Awadalla et al., 2023) pioneered to achieve the goal by constructing large-scale multi-modal datasets and using such data for upstream pretraining. To further adapt the pretrained models to downstream tasks effectively with better in-context learning ability, *Otter* (Li et al., 2023c), an instruction tuning-based method, has been proposed based on OpenFlamingo. These methods involve creating diverse downstream text-image interleaved datasets and integrating them with the multimodal instruction format. To achieve better performance, researchers have been mainly dedicated to dataset construction for instruction tuning, where they show that increasing the dataset size, complexity, and diversity can consistently improve the model performance (Li et al., 2023b). However the importance of the multimodal instruction format is merely studied.

Due to the selection of different tasks for constructing visual instruction datasets, existing methods employ various multimodal instruction formats mainly composed of four components, including in-context demonstrations, instruction, question and answer (shown in Table 1). For example, *Qwen-VL* (Bai et al., 2023) collects traditional vision-language tasks by simply concatenating samples from the same task without any instructions to form the instruction format. Thus, training in this format is essentially performing multi-task learning instead of instruction tuning. *Otter* (Li et al., 2023c) and *MMICL* (Zhao et al., 2023b) improved the process by applying an instance-level instruction format to merge the interleaved datasets for instruction tuning. Despite their success, we argue that the existing instruction-level instruction format has its limitations. One

[1] Anonymous Institution, Anonymous City, Anonymous Region, Anonymous Country. Correspondence to: Anonymous Author <anon.email@domain.com>.

Preliminary work. Under review by the International Conference on Machine Learning (ICML). Do not distribute.

	Model	Text-Image Interleaved Training Data Format
(a)	`MultiInstruct` (Xu et al., 2022)	Image Instruction Question Answer End
(b)	`Flamingo` (Alayrac et al., 2022), `OpenFlamingo` (Awadalla et al., 2023)	… Image Content End
(c)	`Qwen-VL` (Bai et al., 2023)	In-context Exemplars … Image Question Answer End
(d)	`Otter` (Li et al., 2023c), `MMICL` (Zhao et al., 2023b)	In-context Exemplars … Image Instruction Question Answer End
(e)	`UMIT` (Ours)	Definition In-context Exemplars … Image Instruction Question Answer End

Table 1: The existing text-image interleaved instruction formats exhibit variations across different datasets for preserving in-context learning ability. For example, MultiInstruct overlooks in-context demonstrations, whereas Qwen-VL focuses on preserving in-context learning ability without explicit instructions. Moreover, the majority of Otter's datasets are derived from real-world tasks, which means that its questions can be considered a form of instance-level instruction. Similarly, MMICL (Zhao et al., 2023b) incorporates diverse VL tasks and creates instance-level instruction templates for their instances. Distinct from these formats, we propose Unified Multimodal Instruction Tuning (`UMIT`) to unify different formats in various datasets while effectively expanding task diversity and preserving in-context learning ability.

limitation is the inherent lack of task-level contextual understanding. This deficiency poses challenges for the model in comprehending the broader context of the questions it encounters, hindering its ability to swiftly adapt to diverse task domains and provide accurate responses. For instance, *LLaVA* (Liu et al., 2023b) introduces task-level system messages to prompt GPT-4 to accurately generate corresponding visual instruction datasets. Furthermore, it's worth noting that these models are fine-tuned based on foundation models (e.g., OpenFlamingo), which lack instance-level instructions during their pretraining phase. This absence of instance-level instruction introduces a discrepancy between the fine-tuning and pretraining stages, thereby potentially diminishing the efficiency of instruction tuning. Thus, a natural question emerges: "*What should be the multi-modal instruction format for instruction tuning?*" Furthermore, the multi-modal instruction format is the way to merge the collected image-text interleaved data for fine-tuning. In contrast to increasing the data diversity for enhancing the in-context learning ability, is it possible to use less data but with a more effective multi-modal instruction format to improve the model's in-context learning ability?

In this work, we present **U**nified **M**ultimodal **I**nstruction **T**uning (`UMIT`), a general framework to construct a text-image interleaved instruction dataset by merging diverse vision-language tasks in a unified multimodal instruction format. `UMIT` introduces an essential component to construct the multimodal instruction format, namely "task definition" in addition to in-context demonstrations, instance-level instruction, question, and answer and is placed at the forefront. The goal of the task definition is to inform the model about the contextual task-level information and reduce the gap between the format inconsistency between the pretraining and fine-tuning stages. In addition, the inclusion of a task definition can lead to synergistic benefits by leveraging the efforts invested in data construction. For data construction, the main efforts in the literature aim to construct more diverse, complicated, and large datasets. Implicitly, this construction contributes to enhancing task diversity and naturally provides a task definition. As a result, our instruction format effectively harnesses this data, offering the potential to use less data for better performance.

`UMIT` consists of two key steps. It first collects a set of text-image interleaved datasets and then transfers them into the unified multimodal instruction formation for finetuning. We collect data from existing instruction datasets (Xu et al., 2022; Liu et al., 2023b; Gong et al., 2023; Li et al., 2023b; Zhao et al., 2023a), which naturally provide the task descriptions. To evaluate the potential of our method, we only randomly select a few examples for each task. Given the data, we then can convert it into our instruction format. To construct the task definition, since annotations are from different annotators, there exist significant differences in the instructions for different tasks. To reduce the impact of the format inconsistency on combining diverse tasks, we leverage an oracle model (i.e., OpenAI GPT-3.5[1]) to transfer the multimodal instructions of diverse tasks in a unified style. To construct the in-context demonstrations, we employ a retrieval-based approach. The rest of the components all match the corresponding fields in our unified format, so we directly follow their original styles and fill them into our format.

[1] `https://platform.openai.com/docs/models/gpt-3-5`

We conduct comprehensive experiments to evaluate the impact of different multimodal instruction formats on the in-context learning ability of MLLMs (§4.2). Specifically, although we use less data (150k, almost 20 times less than one baseline (*otter*)), our unified format demonstrates average improvements of 4.7 and 9.4 on the MME Benchmark (Fu et al., 2023) and SEED-Bench (Li et al., 2023a), respectively, compared to baselines in the in-context learning setting. Furthermore, We also perform a comprehensive study on three traditional vision-language tasks, analyzing the influence of the components in different formats on in-context learning ability (§4.3). Extensive experimental results show that `UMIT` significantly mitigates the loss of in-context learning capability caused by instruction tuning compared with prior formats, which means it can successfully combine various components into a more effective unified format. For further analysis, we also explore the effects of our proposed unified format on zero-shot performance (§4.4). The results show that our method effectively merges instruction datasets to enhance task diversity without degrading the zero-shot performance.

2. Related Work

Visual Instruction tuning. Progress has been witnessed in transferring the powerful capabilities of instruction tuning to the multimodal domain. MultiInstruct (Xu et al., 2022) is pioneered to collect a large number of vision-language (VL) tasks formatted in **task-level** instructions to improve zero-shot generalization of vision-language models on unseen tasks. With the emergence of multimodal large language models (MLLMs), recent works show interest in constructing high-quality visual instruction datasets with various instruction formats to unlock the potential of MLLMs on both zero- and few-shot generalization. Existing works (Liu et al., 2023b; Zhu et al., 2023; Dai et al., 2023; Chen et al., 2023b;a) prefers to adopt the instruction format that only contains a single image-text pair per sample (Text here generally includes instruction, question, answer), which leads to great zero-shot performance while being attributed to the lack of the in-context learning ability.

Multimodal in-context learning. Flamingo is the pioneering work to support in-context learning in the multi-modal domain by constructing *MultiModal MassiveWeb* (M3W) dataset and employing the upstream training. Following this line of thought, the other works, such as OpenFlamingo (Awadalla et al., 2023), Otter (Li et al., 2023c), Kosmos-1 (Huang et al., 2023), Emu (Sun et al., 2023), OBELICS (Laurençon et al., 2023), and MMICL (Zhao et al., 2023b) focus on constructing text-image interleaved datasets by adding related in-context demonstrations, thus enhancing the in-context learning ability of MLLMs.

Configuring MultiModal In-Context Demonstrations. In VL community, recent studies are exploring how to configure multimodal in-context demonstrations (MICDs) to enhance the in-context learning capabilities of MLLMs in traditional VL tasks. For example, Yang et al. (2023), Li et al. (2023e) and Chen et al. (2023c) utilized different strategies in selecting MICDs for image captioning (IC) and Visual Question Answering (VQA), respectively. Peng et al. (2023) proposed ICD-LM, specifically designed to generate effective MICDs for both IC and VQA tasks. However, these methods have overlooked the impact of the multimodal format. MICDs are just one component of the format, and the arrangement of different components within the format can also affect the multimodal in-context learning capabilities. In this regard, our `UMIT` conduct some explorations.

3. Unified Multimodal Instruction Tuning

In this section, we first detail the key components constituting the existing multimodal instruction formats, along with the recent research advancements as depicted in Table 1. We then introduce the pipeline we used to collect more diverse tasks from different datasets. Last but not least, we present Unified Multimodal Instruction Tuning (`UMIT`), a pioneering attempt to unify the multimodal instruction format that both preserves in-context learning capabilities and assists in merging various visual instruction datasets to enhance task diversity.

3.1. Preliminaries on Multimodal Instruction Format

Flamingo (Alayrac et al., 2022) and Open-Flamingo (Awadalla et al., 2023) emerge as pioneering frameworks to address a diverse spectrum of vision-language tasks, encompassing visual question-answering, captioning, and image classification. Initially, the design exclusively incorporated the **demonstrations** to support in-context learning. Formally, given a new instance i, the instruction format $\mathcal{F}^i$ employed by Flamingo and OpenFlamingo is expressed as:

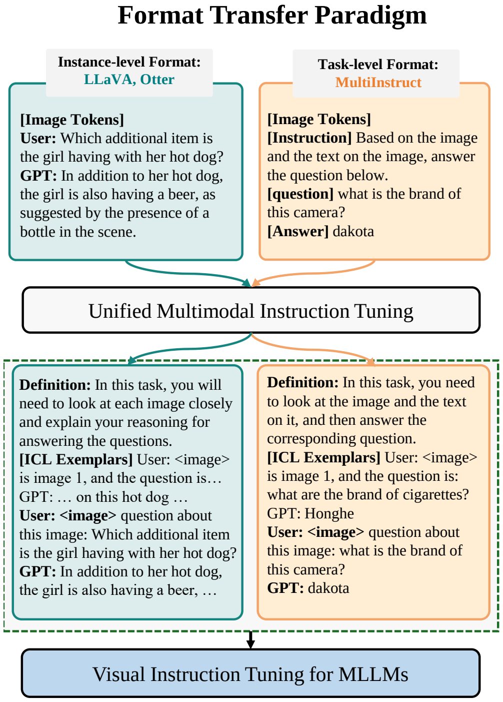
$$\mathcal{F}_0^i = (\ [\mathbf{X}_{\mathrm{e}}^1, \cdots, \mathbf{X}_{\mathrm{e}}^N],\ \mathbf{X}_{\mathrm{v}}^i,\ \mathbf{X}_{\mathrm{l}}^i), \tag{1}$$

wherein, for instance i, in-context demonstrations $\mathbf{X}_{\mathrm{e}}^j$ are randomly selected to construct few-shot templates, while $\mathbf{X}_{\mathrm{v}}^i$ and $\mathbf{X}_{\mathrm{l}}^i$ denote the image and language content of instance i, respectively.

As delineated in Table 1, Qwen-VL (Bai et al., 2023) took the initiative to extend the framework to encompass three components. It notably segregates the language input into **question** and **answer** for the current instance, denoted as $\mathbf{X}_{\mathrm{q}}^i$ and $\mathbf{X}_{\mathrm{a}}^i$, respectively. The overall format thus evolves to:

$$\mathcal{F}_1^i = (\ [\mathbf{X}_{\mathrm{e}}^1, \cdots, \mathbf{X}_{\mathrm{e}}^N],\ \mathbf{X}_{\mathrm{v}}^i,\ \mathbf{X}_{\mathrm{q}}^i,\ \mathbf{X}_{\mathrm{a}}^i\ ). \tag{2}$$

Moreover, unlike the format utilized by Qwen-VL, Otter (Li et al., 2023c) and MMICL (Zhao et al., 2023b) incorporated



[Image Tokens]
User: Which additional item is the girl having with her hot dog?
GPT: In addition to her hot dog, the girl is also having a beer, as suggested by the presence of a bottle in the scene.

[Image Tokens]
[Instruction] Based on the image and the text on the image, answer the question below.
[question] what is the brand of this camera?
[Answer] dakota

Definition: In this task, you will need to look at each image closely and explain your reasoning for answering the questions.
[ICL Exemplars] User: <image> is image 1, and the question is…
GPT: … on this hot dog …
User: <image> question about this image: Which additional item is the girl having with her hot dog?
GPT: In addition to her hot dog, the girl is also having a beer, …

Definition: In this task, you need to look at the image and the text on it, and then answer the corresponding question.
[ICL Exemplars] User: <image> is image 1, and the question is: what are the brand of cigarettes?
GPT: Honghe
User: <image> question about this image: what is the brand of this camera?
GPT: dakota

Figure 1: Multimodal instruction format transfer paradigm.

the instance-level instruction component ($\mathbf{X}_{\mathtt{i}}^i$) into the prompt format design for in-context instruction tuning, thereby enriching the overall format to become:

$$\mathcal{F}_2^i = ([\mathbf{X}_{\mathtt{e}}^1, \cdots, \mathbf{X}_{\mathtt{e}}^N],\ \mathbf{X}_{\mathtt{v}}^i,\ \mathbf{X}_{\mathtt{i}}^i,\ \mathbf{X}_{\mathtt{q}}^i,\ \mathbf{X}_{\mathtt{a}}^i\ ). \tag{3}$$

Therefore, the current state-of-the-art multimodal instruction formats encapsulate four components: 1) **demonstrations**, 2) **instruction**, 3) **question**, and 4) **answer** corresponding to the current instance or context. As elucidated in Section 1, prevailing literature predominantly focuses on instance-level instruction tuning, which is highly specific to each data sample. Nonetheless, a high-level task-level orientation has been conspicuously overlooked. As shown in Table 1 (d), we devise a new component, **task definition**, to bridge this gap in our UMIT, which will be elaborated in Section 3.3. Additionally, we discern that the current demonstrations are selected through various methods. We then further explore the influence of different demonstration retrieval methods on in-context learning, thus selecting the most effective demonstrations to augment the performance further.

3.2. Data Collection Pipline for UMIT

As our task definition prompt and enhanced demonstration generation requires a prebuilt database, we first introduce the data collection pipeline. We conduct data collection and construction through the following three steps.

Step i Data Collection First, we gathered various datasets containing different tasks (55 in total), categorizing them into five main types, including image caption (IC), visual question answering (VQA), visual reasoning (VR), referential dialogue (RD), and language-only tasks. Detailed information about data resources can be found in Appendix A.

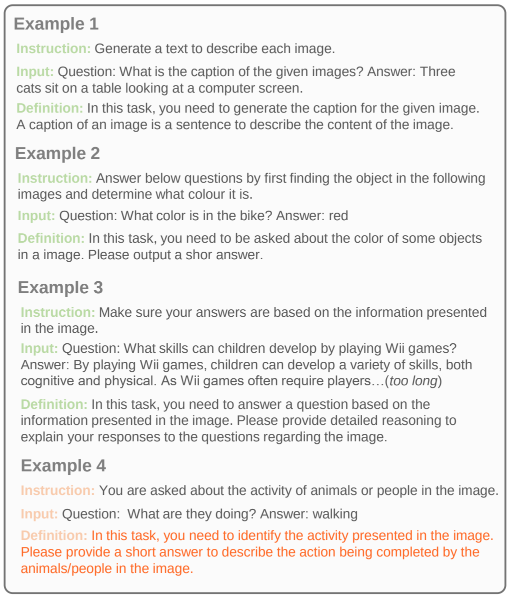
Step ii Format Transfer For the tasks within these different data resources, we organize their task-specific instructions and notice significant format discrepancies among them. Directly merging them would diminish the in-context learning ability on unseen tasks due to format inconsistency. Therefore, we transfer these instructions into a unified style of task definition.

Step iii Data Filiter During the training process, we employ filtering strategies described in Appendix C to further reduce the effects of increasing dataset scale while preserving the benefits of increasing task diversity.

3.3. Task Definition as a Novel Component in Format

Foundation models, pre-trained on massive data harvested from a multitude of sources, have exhibited formidable capabilities in generating insightful responses. Yet, there remains a margin for enhancement in terms of accuracy and professionalism. Various methods of instruction tuning have been proffered as a means to steer these models towards more precise outcomes. However, a notable limitation lies in the fact that such instructions tend to be instance-specific, as opposed to being driven by the overarching task at hand. This narrow focus could potentially hamstring the model's ability to generalize across a broader spectrum of queries, thereby underscoring the necessity for more holistic, task-oriented tuning methodologies. Adopting a more task-centric approach may pave the way for more adept handling of queries, propelling the model towards generating answers that are not only accurate but are imbued with a higher degree of professionalism.

Inspired by the above observations, we propose to improve the instruction tuning by introducing our **task definition** in UMIT. Denote the original task-level instruction as $\mathcal{I}$. We aim to transfer $\mathcal{I}$ of any style to a more unified task definition $\mathcal{D}$, to constrain learning task-specific information contained in the in-context demonstrations. Inspired by Liang et al. (2023), we employ GPT-3.5 (text-davinci-003) as the Oracle model f_{oracle} to transfer different styles of task-level instructions into task definitions with a unified style for each task via in-context learning. Specifically, k seed instruction-exemplar pairs $\{(\mathbf{X}_{\mathtt{i}}^1, \mathbf{X}_{\mathtt{e}}^1), \ldots, (\mathbf{X}_{\mathtt{i}}^k, \mathbf{X}_{\mathtt{e}}^k)\}$ are manually selected from several tasks. Then we craft a task definition $\mathcal{D}_j$ for each instruction-demonstration pair $(\mathbf{X}_{\mathtt{i}}^j, \mathbf{X}_{\mathtt{e}}^j)$, and consequently get a set of instruction-demonstration-definition pairs $\{(\mathbf{X}_{\mathtt{i}}^1, \mathbf{X}_{\mathtt{e}}^1, \mathcal{D}_1), \ldots, (\mathbf{X}_{\mathtt{i}}^k, \mathbf{X}_{\mathtt{e}}^k, \mathcal{D}_k)\}$, which is used as the prompt for the Oracle model. Then, given a new instruction-demonstration pair $(\mathbf{X}_{\mathtt{i}}^{\mathtt{new}}, \mathbf{X}_{\mathtt{e}}^{\mathtt{new}})$, the Oracle model will generate the corresponding unified-style task definition $\mathcal{D}_{\mathtt{new}}$ as follows:



Example 1

Instruction: Generate a text to describe each image.

Input: Question: What is the caption of the given images? Answer: Three cats sit on a table looking at a computer screen.

Definition: In this task, you need to generate the caption for the given image. A caption of an image is a sentence to describe the content of the image.

Example 2

Instruction: Answer below questions by first finding the object in the following images and determine what colour it is.

Input: Question: What color is in the bike? Answer: red

Definition: In this task, you need to be asked about the color of some objects in a image. Please output a shor answer.

Example 3

Instruction: Make sure your answers are based on the information presented in the image.

Input: Question: What skills can children develop by playing Wii games? Answer: By playing Wii games, children can develop a variety of skills, both cognitive and physical. As Wii games often require players…(*too long*)

Definition: In this task, you need to answer a question based on the information presented in the image. Please provide detailed reasoning to explain your responses to the questions regarding the image.

Example 4

Instruction: You are asked about the activity of animals or people in the image.

Input: Question: What are they doing? Answer: walking

Definition: In this task, you need to identify the activity presented in the image. Please provide a short answer to describe the action being completed by the animals/people in the image.

Figure 2: An example of generating a task definition in a unified style. To obtain more accurate definitions, we incorporate in-context demonstrations in our prompts.

$$\mathcal{D}_{\texttt{new}} = f_{oracle}\,[\,(\mathbf{X}_{\texttt{i}}^{1}, \mathbf{X}_{\texttt{e}}^{1}, \mathcal{D}_1), \ldots, (\mathbf{X}_{\texttt{i}}^{k}, \mathbf{X}_{\texttt{e}}^{k}, \mathcal{D}_k), \tag{4}$$

$$(\mathbf{X}_{\texttt{i}}^{\texttt{new}}, \mathbf{X}_{\texttt{e}}^{\texttt{new}})\,]\,. \tag{5}$$

As shown in Tabel 1 (right), we assist GPT-3.5 in better understanding task types by incorporating task instances, such as distinguishing between tasks that require long answers (e.g., LLaVA-instruction-150k (Liu et al., 2023b)) and those that require short answers (e.g., GQA (Hudson & Manning, 2019)). However, we contend that creating a robust and meaningful definition for each instance from real-world scenarios is an ongoing challenge that requires further exploration in the future.

3.4. Enhanced Demonstrations Configuration to Boost In-Context Learning

Prior works in multimodal domains (Yang et al., 2022; Li et al., 2023c; Bai et al., 2023; Zhao et al., 2023b) have shown that adding in-context demonstrations can preserve the model's in-context learning capabilities. However, the impact of different in-context demonstration selection approaches on in-context learning ability remains an under-explored facet. Therefore, in this section, we comprehensively investigate the selection of in-context demonstrations using both image and text features. Specifically, We define $C = \{T_1, T_2, \ldots, T_N\}$ as the retrieval database, which is a collection of N vision-language tasks, where each task $T = \{(\mathbf{X}_{\texttt{v}}^{1}, \mathbf{X}_{\texttt{q}}^{1}, \mathbf{X}_{\texttt{a}}^{1}), \ldots, (\mathbf{X}_{\texttt{v}}^{n}, \mathbf{X}_{\texttt{q}}^{n}, \mathbf{X}_{\texttt{a}}^{n})\}$ is a dataset consisting of n image-question-answer pairs collected in Section 3.2.

For data retrieval, we denote $\mathbf{Z}_{\texttt{e}} = (\mathbf{X}_{\texttt{v}}, \mathbf{X}_{\texttt{q}}, \mathbf{X}_{\texttt{a}})$ as a retrieval demonstration, and use an image encoder $\mathbf{E}_{\texttt{Image}}$ and a text encoder $\mathbf{E}_{\texttt{Text}}$, mapping a text or image instance to a d-dimensional latent space. Then, we select in-context demonstrations based on the cosine similarity of their representations. Specifically, we initialize the image encoder with CLIP-ViT (Radford et al., 2021), a pretrained vision transformer, and we employ `text-embedding-ada-002` [2] as the text encoder. Therefore, for a new demonstration $\mathbf{Z}_{\texttt{e}}^{\texttt{new}} = (\mathbf{X}_{\texttt{v}}^{\texttt{new}}, \mathbf{X}_{\texttt{q}}^{\texttt{new}}, \mathbf{X}_{\texttt{a}}^{\texttt{new}})$ belonging to task T, we respectively searches k nearest samples in both text-encoded and image-encoded latent space, according to the cosine similarity. We denote this retrieval pipeline as $\mathcal{R}$:

$$\mathcal{R}(\mathbf{Z}_{\texttt{e}}^{\texttt{new}}) = \{\underset{\mathbf{Z}_{\texttt{e}}}{\text{Top}\,k}\,(\mathbf{E}_{\texttt{Img}}(\mathbf{Z}_{\texttt{e}}^{\texttt{new}}) \cdot \mathbf{E}_{\texttt{Img}}(\mathbf{Z}_{\texttt{e}}))\,, \tag{6}$$

$$\underset{\mathbf{Z}_{\texttt{e}}}{\text{Top}\,k}\,(\mathbf{E}_{\texttt{Text}}(\mathbf{Z}_{\texttt{e}}^{\texttt{new}}) \cdot \mathbf{E}_{\texttt{Text}}(\mathbf{Z}_{\texttt{e}}))\} \tag{7}$$

$$= \{\hat{\mathbf{Z}}_{\texttt{e}}^{1}, \ldots, \hat{\mathbf{Z}}_{\texttt{e}}^{2k}\}. \tag{8}$$

Where $\mathbf{E}_{\texttt{Text}}$ use the $\mathbf{X}_{\texttt{i}}$, $\mathbf{X}_{\texttt{q}}$ and $\mathbf{X}_{\texttt{a}}$ to compute the text embedding during the training stage.

3.5. Unified multimodal instruction format

Based on the diverse tasks collected as mentioned above, along with specific task definitions and in-context demonstrations, we propose a unified multimodal instruction format $\mathcal{F}_3$:

$$\mathcal{F}_3 = (\mathcal{D}_{\texttt{new}}, [\mathbf{X}_{\texttt{e}}^{1}, \ldots, \mathbf{X}_{\texttt{e}}^{N}], \mathbf{X}_{\texttt{v}}^{\texttt{new}}, \mathbf{X}_{\texttt{i}}^{\texttt{new}}, \mathbf{X}_{\texttt{q}}^{\texttt{new}}, \mathbf{X}_{\texttt{a}}^{\texttt{new}}). \tag{9}$$

Where $\mathcal{D}_{\texttt{new}}$ denotes the unified task definition generated by prompting the Oracle model as Eq. 4. Note that for each instance j, the in-context demonstration consists of $(\hat{\mathbf{X}}_{\texttt{v}}^{j}, \mathbf{X}_{\texttt{i}}^{i}, \hat{\mathbf{X}}_{\texttt{q}}^{j}, \hat{\mathbf{X}}_{\texttt{a}}^{j})$, where $(\hat{\mathbf{X}}_{\texttt{v}}^{j}, \hat{\mathbf{X}}_{\texttt{q}}^{j}, \hat{\mathbf{X}}_{\texttt{a}}^{j}) = \mathcal{R}((\mathbf{X}_{\texttt{v}}^{\texttt{new}}, \mathbf{X}_{\texttt{q}}^{\texttt{new}}, \mathbf{X}_{\texttt{a}}^{\texttt{new}}))_j$ is the j-th retrieved demonstration.

4. Experiments

4.1. General Setup

Format and Baselines. These instruction formats primarily consist of five components, as referenced in Section 3.1: (1) task definition (**D**), (2) in-context examples (**E**), (3) instruction (**I**) that is customized for individual example, (4) Question of the current instance (**Q**), (5) Answer of the current instance (**A**). We can map these components into the existing baselines. Since we mainly focus on the in-context learning ability, we mainly consider the methods following the directions of Flamingo as baselines, which include: **(1) OpenFlamingo** (Awadalla et al., 2023), which

[2] https://platform.openai.com/docs/guides/embeddings/what-are-embeddings

Models	#Exp	Shots	Existen.	Count	Pos.	Color	Poster	Cele.	Scene	Land.	Art.	OCR	Perception
OpenFlamingo†	-	0	103.33	43.33	60.00	55.00	111.56	91.76	95.25	54.75	78.50	55.00	748.50
OpenFlamingo†	-	2	150.00	58.33	63.33	75.00	89.46	56.18	108.50	50.00	79.25	70.00	800.05
OpenFlamingo†	-	4	145.00	55.00	63.33	85.00	84.35	60.59	125.50	50.00	94.50	95.00	858.28
Otter†	2.8M	0	185.00	88.33	65.00	113.33	117.69	110.29	162.25	99.50	105.25	50.00	1096.65
Otter†	2.8M	2	**190.00**	**125.00**	55.00	75.00	119.39	121.47	159.25	105.25	109.00	57.50	1116.86
Otter†	2.8M	4	**190.00**	100.00	60.00	85.00	113.27	115.88	149.75	105.25	96.50	72.50	1088.15
OpenFlamingo ($\mathcal{F}_1$)	148k	0	165.00	78.33	56.67	125.00	120.07	105.29	140.75	94.50	72.25	72.50	1030.36
OpenFlamingo ($\mathcal{F}_1$)	148k	2	175.00	91.67	63.33	125.00	150.00	125.88	158.75	123.00	113.25	80.00	1205.88
OpenFlamingo ($\mathcal{F}_1$)	148k	4	175.00	83.33	60.00	125.00	**158.16**	135.88	157.75	122.25	109.75	80.00	1207.13
Otter ($\mathcal{F}_2$)	148k	0	180.00	100.00	75.00	120.00	81.63	52.65	131.75	59.00	72.25	50.00	922.28
Otter ($\mathcal{F}_2$)	148k	2	180.00	73.33	75.00	108.33	147.28	162.94	**168.25**	**147.75**	99.50	80.00	1242.39
Otter ($\mathcal{F}_2$)	148k	4	180.00	48.33	56.67	100.00	150.00	127.65	166.75	144.00	84.25	80.00	1137.65
UMIT ($\mathcal{F}_3$)	148k	0	180.00	53.33	48.33	103.33	138.10	129.41	157.25	126.00	95.00	65.00	1095.76
UMIT ($\mathcal{F}_3$)	148k	2	180.00	108.33	**90.00**	118.33	148.30	161.18	160.75	145.50	**122.75**	102.50	**1337.64**
UMIT ($\mathcal{F}_3$)	148k	4	185.00	98.33	70.00	**130.00**	154.42	**163.82**	161.50	146.50	116.00	**102.50**	1328.08

Table 2: Zero- and Few-shot evaluation of coarse-grained and fine-grained recognition and OCR on MME Benchmark (Fu et al., 2023). Models with † refer to our measure while indicating the results reported from their paper. Otter ($\mathcal{F}_2$) refers that we instruction fine-tune OpenFlamingo by employing the format used by Otter sytle ($\mathcal{F}_2$) mentioned in Equation 3).

Models	#Exp	Shots	Scene	Identity	Attr.	Loc.	Count.	Spatial	Interac.	Reason.	Text Rec.	Avg.
OpenFlamingo†	-	0	55.1	49.5	47.9	37.4	37.8	33.8	40.2	43.2	30.6	46.3
OpenFlamingo†	-	2	55.6	51.3	49.6	39.3	42.1	32.7	43.3	45.3	44.7	48.2
OpenFlamingo†	-	4	56.9	51.8	50.1	38.6	43.7	32.7	44.3	43.8	45.9	48.9
Otter†	2.8M	0	56.6	51.2	49.4	38.9	39.6	35.3	41.2	45.9	30.6	47.9
Otter†	2.8M	2	55.3	51.2	49.8	39.3	42.7	32.9	45.4	46.5	44.7	48.3
Otter†	2.8M	4	54.7	50.8	49.2	39.2	42.2	32.6	45.4	45.6	44.7	47.9
OpenFlamingo ($\mathcal{F}_1$)	148k	0	55.9	54.2	57.8	42.9	47.6	39.0	48.5	45.3	**48.2**	52.9
OpenFlamingo ($\mathcal{F}_1$)	148k	2	57.9	56.2	62.0	44.6	50.6	41.9	53.6	46.5	43.5	55.7
OpenFlamingo ($\mathcal{F}_1$)	148k	4	58.0	55.5	61.4	43.3	51.5	40.2	51.6	47.1	38.8	55.4
Otter ($\mathcal{F}_2$)	148k	0	61.2	56.6	62.0	45.3	50.0	42.5	52.6	49.2	28.2	56.5
Otter ($\mathcal{F}_2$)	148k	2	59.3	55.6	62.0	45.7	53.3	42.3	54.6	46.8	28.2	56.4
Otter ($\mathcal{F}_2$)	148k	4	60.0	56.2	**62.4**	45.9	**53.8**	42.8	54.6	47.7	28.2	57.0
UMIT ($\mathcal{F}_3$)	148k	0	**62.6**	57.1	59.2	**47.8**	49.9	38.7	**56.7**	50.2	38.2	56.1
UMIT ($\mathcal{F}_3$)	148k	2	61.5	**58.0**	61.9	47.0	52.5	42.8	53.6	**52.6**	30.6	57.3
UMIT ($\mathcal{F}_3$)	148k	4	61.5	57.6	62.0	45.3	53.3	**43.1**	50.5	50.5	36.5	**57.3**

Table 3: Zero- and Few-shot evaluation on SEED-Bench (Li et al., 2023a) consists of 19K multiple-choice questions with accurate human annotations, covering 12 evaluation dimensions including both the spatial and temporal understanding.

is an open-sourced Flamingo (Alayrac et al., 2022) with an internal LLM of MPT-7b. The instruction format is composed of EQA. **(2) Otter** (Li et al., 2023c) is trained on OpenFlamingo with MIMIC-IT datasets (including 2.8M samples) (Li et al., 2023b) and first introduces in-context learning into visual instruction tuning. The instruction format is composed of $EIQA$.

Hyper-parameter and Training Details. We train `UMIT` on our proposed dataset in `UMIT` format ($\mathcal{F}_3$). We utilize DeepSpeed (Rasley et al., 2020) for optimization during the training process. The AdamW (Loshchilov & Hutter, 2018) optimizer is used, with $\beta_1 = 0.9, \beta_2 = 0.999$, and a weight decay of 0.01. All training runs on 4 NVIDIA A100 GPUs, with a total batch size of 128, a learning rate of 2×10^{-5} for the second stage. Details can be found in Appendix C.

4.2. Evaluation on Multi-modal Benchmarks

To evaluate the effectiveness of our method, here, we select two commonly employed benchmarks: MME(Fu et al., 2023) and SEED (Li et al., 2023a). As we aim to assess the in-context learning ability, we evaluate the performance by using k example as an in-context demonstrations, where $k = \{0,2,4\}$. We compare our method with the officially released checkpoint and denote the baselines as OpenFlamingo† and Otter†. Since the baseline methods are trained on different sizes of instruction data compared to ours, for a fair comparison, we also apply the baselines on our training corpus with their instruction tuning format. We denote them as OpenFlamingo ($\mathcal{F}_1$) and Otter ($\mathcal{F}_2$).

4.2.1. Experiment Results on MME Benchmark

We conducted comprehensive testing on the MME Benchmark (Fu et al., 2023) to assess the impact of different formats and task diversity on the zero- and few-shot capabilities of our models. The MME Benchmark is a comprehensive multimodal benchmark used to evaluate the abilities of MLLMs across 14 tasks. It can be divided into perception and cognition benchmarks. Each task in the cognition benchmark contains only 20 examples, which can result in high

Data	Retrieval	HatefulMemes (Kiela et al., 2020)				VizWiz (Gurari et al., 2018)				ISEKAI (Tai et al., 2023)			
Format	Method	$k=0$	$k=2$	$k=4$	$k=8$	$k=0$	$k=2$	$k=4$	$k=8$	$k=0$	$k=4$	$k=8$	$k=16$
EQA ($\mathcal{F}_1$)	mixed	51.40	50.70	54.00	51.30	11.91	16.54	28.91	**45.71**	0.18	0.48	0.57	0.54
EIQA ($\mathcal{F}_2$)	mixed	54.44	54.57	53.89	50.56	24.74	28.93	29.38	30.90	0.00	0.38	0.46	0.58
EIQA ($\mathcal{F}_2$)	image	57.79	53.67	51.94	51.98	22.99	28.95	30.10	30.16	0.01	0.40	0.48	0.50
EIQA ($\mathcal{F}_2$)	text	56.76	55.10	56.96	55.52	17.13	27.58	28.27	30.01	0.00	0.37	0.51	0.53
Testing-time Format Transfer													
DEIQA ($\mathcal{F}_3$)	image	55.11	54.58	54.28	54.36	26.13	32.69	33.66	35.42	0.25	0.42	0.51	0.57
DEIQA ($\mathcal{F}_3$)	text	59.38	**56.66**	57.80	54.94	26.54	31.68	31.40	32.28	0.00	0.41	0.54	0.57
Training time Format Transfer													
DEIQA ($\mathcal{F}_3$)	random	61.37	54.15	52.49	50.61	27.15	29.53	30.66	31.21	0.18	0.47	0.56	0.64
DEIQA ($\mathcal{F}_3$)	image	59.09	55.57	55.94	56.88	**27.45**	32.69	33.75	34.95	**0.32**	**0.51**	**0.62**	0.67
DEIQA ($\mathcal{F}_3$)	text	57.96	55.69	**60.19**	**59.18**	26.79	**33.55**	**36.06**	37.60	0.22	0.47	0.57	0.65
DEIQA ($\mathcal{F}_3$)	mixed	**61.86**	54.65	55.78	51.77	27.03	29.66	31.02	31.87	0.20	0.41	0.61	**0.84**

Table 4: Comparison of different multimodal instruction formats on few-shot evaluation. k is the number of in-context examples that are randomly selected in the inference stage. EQA, EIQA, and UMIT respectively represent the ways of constructing text-image interleaved data based on OpenFlamingo ($\mathcal{F}_1$), Otter ($\mathcal{F}_2$), and UMIT ($\mathcal{F}_3$). "Testing-time Format Transfer" refers that we train the model in format ($\mathcal{F}_2$) while testing the model in format ($\mathcal{F}_3$). "Training time Format Transfer" means that we train and test the model both in format ($\mathcal{F}_3$).

variance in the evaluation of different checkpoints. Therefore, we only evaluate our models on the perception benchmark, which consists of 10 tasks: existence, count, position, color, posters, celebrities, scenes, landmarks, and artworks.

Specifically, as shown in Table 2, we can find that: (1) Compared with other MLLMs that also emphasize in-context learning, such as OpenFlamingo (Awadalla et al., 2023) and Otter (Li et al., 2023c), UMIT, trained on datasets merged through our unified format, has demonstrated superior performance in terms of in-context learning capabilities. (2) Due to the training dataset used by Otter being predominantly composed of real-world VL tasks while lacking traditional VL tasks (Li et al., 2023b), UMIT, which is trained on a more diverse dataset, manages to attain a comparable performance while utilizing only 5% of its data volume. (3) For a fair comparison between different multimodal instruction formats, we also introduce OpenFlamingo ($\mathcal{F}_1$) and Otter ($\mathcal{F}_2$), which are trained on our dataset while preserving their own instruction formats. The results again demonstrate that UMIT can improve both zero- and few-shot task generalization performance by unifying the multimodal instruction format.

4.2.2. Experiment Results on SEED-Bench

We further evaluate the impact of various instruction formats on SEED-Bench (Li et al., 2023a), a benchmark consisting of 19K multiple choice questions with accurate human annotations including both spatial and temporal comprehension. We choose the spatial benchmark for our evaluation, which includes 9 tasks (number of included examples): Scene Understanding (3158), Instance Identity (1831), Instance Attribute (4649), Instance Location (978), Instance Counting (2447), Spatial Relation (657), Instance Interaction (97), Visual Reasoning (331), and Text Recognition (85).

Results are shown in Table 3, and we obtain conclusions similar to those on the MME benchmark: (1) in-context learning: UMIT outperforms all existing OpenFlamingo-based MLLMs in the 4-shot setting and also surpasses two other models trained on existing formats used to construct text-image interleaved datasets. (2) task diversity: Compared to OpenFlamingo and Otter, UMIT exhibits a significant advantage in both zero- and few-shot performance. This suggests that merging different datasets by unifying the instruction format does indeed effectively increase task diversity.

4.3. Ablation study

Effects of multimodal instruction formats on in-context learning. As shown in Table 4, we evaluate a total of three different multimodal instruction formats, including EQA, EIQA, DEIQA, on three vision-language tasks (HatefulMemes (Kiela et al., 2020), VizWiz (Gurari et al., 2018), ISEKAI (Tai et al., 2023)).

The results demonstrate that during both test and training times, UMIT is the most effective format for improving in-context learning. Firstly, we observe a decrease in in-context learning ability by transferring EQA format to EIQA format. In the highest shot setting for the two tasks, there is a decrease of 0.74 and 14.81, respectively. We contend this is due to the incorporation of instructions, which widens the gap between visual instruction tuning and pertaining in OpenFlamingo. Secondly, we train on the EIQA format but transfer the test samples to the UMIT format at test time. In the highest shot setting, there is an improvement of 2.38, 5.26, and 0.07 for each of the three tasks, respectively. Finally, when we employ the UMIT format during both training and testing stages, there is a significant improvement compared to the EQA and EIQA baselines in almost all settings.

	Random	Raw	UMIT
MME Perception	1031.61	1057.57	**1095.76**

Table 5: “UMIT” represents we employ task definitions shown in Appendix 11. “Raw” indicates that we set the task definitions for all 10 tasks on the MME benchmark as: “In this task, you need to look at the following images and answer the corresponding question.” “Random” signifies that we randomly assigned the 10 task definitions shown in Table 12 to the 10 tasks on the MME benchmark.

In-context demonstration configuration based on different features. We also conduct a study about the retrieval method using different features (including image and text). random means we randomly select in-context demonstrations to form the UMIT format, while image and text represent the in-context demonstrations selected by image and text features, respectively (Section 3.4). And mixed includes in-context demonstrations in image and text. Based on the results in Table 4, we conclude that the unified format composed of in-context demonstrations retrieved through different features has a different impact on in-context learning in various downstream tasks. For example, in the HatefulMemes task, the model needs to assess whether the text in the meme is hateful, and this text is provided in the instruction, which means instruction is the more important part of in-context. Therefore, we observe that a unified format composed of text in-context demonstrations is more helpful for in-context learning ability on this task.

Quality and robustness of Task Definition. To assess the impact of task definition quality on overall performance, taking into account cost and efficiency, we only adjust the task definition quality during the testing stage for tasks in the MME benchmark. As shown in Table 5, task definition quality has an impact on overall performance. However, this is observed under relatively extreme conditions, leading us to believe that task definitions, after manual inspection, exhibit robustness, especially for diverse real-world tasks.

4.4. Further Analysis

Enhancing task diversity with the unified format. To explore whether the UMIT can effectively merge different tasks by unifying the instruction format to enhance task diversity, we design a set of experiments. Specifically, we first randomly select 8 VQA tasks from our collection of 55 tasks (denoted as vqa). Then We choose another 8 different VQA tasks, denoted as same and 8 tasks distinct from VQA, denoted as diff. By freely combining these three groups of tasks using UMIT, we can obtain different training sets. The results are shown in Figure 3, we can observe that vqa+same+diff achieve the best performance across different shot settings in 4 tasks, suggesting that UMIT can indeed enhance zero- and few-shot performance by merging different tasks.

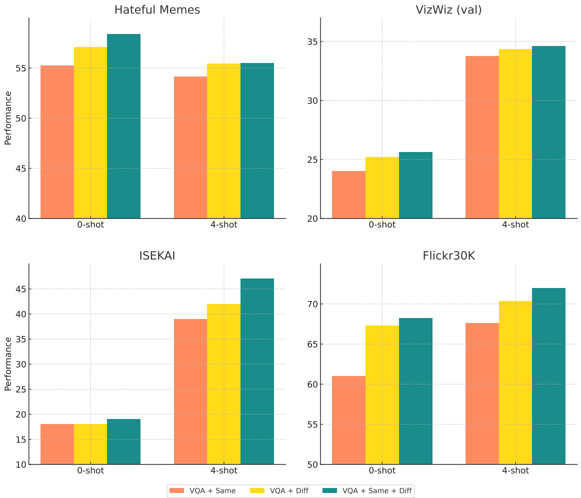


Figure 3: Experiments for enhancing task diversity. We set the dataset to vqa+same, vqa+diff, or vqa+same+diff in format ($\mathcal{F}_3$) and select the in-context demonstrations through the text retrieval method.

The impact of UMIT format on the zero-shot performance. Table 6 shows the comparison between UMIT and some similar MLLMs on Flickr30K, ScienceQA, OK-VQA, and TextVQA tasks. The results suggest that UMIT is ahead of the MLLMs based on OpenFlamingo, so we believe that UMIT has minimal impact on zero-shot performance.

Models	Flickr 30K	SciQA-image	OKVQA	TextVQA
Flamingo-9B	61.5	-	**44.7**	31.8
OpenFlamingo-9B	59.5	-	37.8	24.2
Otter†	63.6	-	42.3	27.2
InstructBLIP-7B	**82.4**	60.5	-	-
UMIT	70.2	**60.9**	43.3	**33.0**

Table 6: Zero-shot evaluation was conducted across multiple datasets, including Flickr30K, ScienceQA (Following Dai et al. (2023), we only evaluate on the set with image context), OK-VQA, and TextVQA. The results confirm that our UMIT does not have an impact on zero-shot performance.

5. Conclusion

In this paper, we propose the unified multimodal instruction tuning framework (UMIT) to merge diverse tasks with limited data by unifying instructions with different styles from various datasets, thus effectively enhancing in-context learning ability. The results show that our designed format has significant advantages over prior formats in in-context learning on various vision-language tasks and benchmarks. In general, we investigate a relatively unexplored facet, i.e., how to construct the text-image interleaved instruction datasets for preserving in-context learning ability, and we anticipate that our research could encourage further exploration in this area.

Societal Impact

Our method, focusing on multimodal in-context learning with pretrained vision-language models (VLMs), boosts rapid adaptation and in-context learning capabilities of VLMs without adding pretrained data biases or ethical dilemmas. However, we acknowledge that the responses depend on user prompts, input images, and pretrained VLMs, which may raise privacy or misuse concerns, yet these issues are beyond the scope of our current work.

References

Alayrac, J.-B., Donahue, J., Luc, P., Miech, A., Barr, I., Hasson, Y., Lenc, K., Mensch, A., Millican, K., Reynolds, M., et al. Flamingo: a visual language model for few-shot learning. *Advances in Neural Information Processing Systems*, 35:23716–23736, 2022.

Amini, A., Gabriel, S., Lin, S., Koncel-Kedziorski, R., Choi, Y., and Hajishirzi, H. MathQA: Towards interpretable math word problem solving with operation-based formalisms. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pp. 2357–2367, Minneapolis, Minnesota, June 2019. Association for Computational Linguistics. doi: 10.18653/v1/N19-1245. URL https://aclanthology.org/N19-1245.

Awadalla, A., Gao, I., Gardner, J., Hessel, J., Hanafy, Y., Zhu, W., Marathe, K., Bitton, Y., Gadre, S., Sagawa, S., et al. Openflamingo: An open-source framework for training large autoregressive vision-language models. *arXiv preprint arXiv:2308.01390*, 2023.

Bai, J., Bai, S., Yang, S., Wang, S., Tan, S., Wang, P., Lin, J., Zhou, C., and Zhou, J. Qwen-vl: A frontier large vision-language model with versatile abilities. *arXiv preprint arXiv:2308.12966*, 2023.

Chen, D., Liu, J., Dai, W., and Wang, B. Visual instruction tuning with polite flamingo. *arXiv preprint arXiv:2307.01003*, 2023a.

Chen, K., Zhang, Z., Zeng, W., Zhang, R., Zhu, F., and Zhao, R. Shikra: Unleashing multimodal llm's referential dialogue magic. *arXiv preprint arXiv:2306.15195*, 2023b.

Chen, S., Han, Z., He, B., Buckley, M., Torr, P., Tresp, V., and Gu, J. Understanding and improving in-context learning on vision-language models. *arXiv preprint arXiv:2311.18021*, 2023c.

Conover, M., Hayes, M., Mathur, A., Xie, J., Wan, J., Shah, S., Ghodsi, A., Wendell, P., Zaharia, M., and Xin, R. Free dolly: Introducing the world's first truly open instruction-tuned llm, 2023. URL https://www.databricks.com/blog/2023/04/12/dolly-first-open-commercially-viable-instruction-

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

Das, A., Kottur, S., Gupta, K., Singh, A., Yadav, D., Moura, J. M., Parikh, D., and Batra, D. Visual dialog. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 326–335, 2017.

Duanmu, Z., Liu, W., Wang, Z., and Wang, Z. Quantifying visual image quality: A bayesian view. *Annual Review of Vision Science*, 7(1):437–464, 2021.

Fu, C., Chen, P., Shen, Y., Qin, Y., Zhang, M., Lin, X., Qiu, Z., Lin, W., Yang, J., Zheng, X., et al. Mme: A comprehensive evaluation benchmark for multimodal large language models. *arXiv preprint arXiv:2306.13394*, 2023.

Ghosal, D., Chia, Y. K., Majumder, N., and Poria, S. Flacuna: Unleashing the problem solving power of vicuna using flan fine-tuning. *arXiv preprint arXiv:2307.02053*, 2023.

Gong, T., Lyu, C., Zhang, S., Wang, Y., Zheng, M., Zhao, Q., Liu, K., Zhang, W., Luo, P., and Chen, K. Multimodal-gpt: A vision and language model for dialogue with humans. *arXiv preprint arXiv:2305.04790*, 2023.

Goyal, Y., Khot, T., Summers-Stay, D., Batra, D., and Parikh, D. Making the v in vqa matter: Elevating the role of image understanding in visual question answering. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 6904–6913, 2017.

Gurari, D., Li, Q., Stangl, A. J., Guo, A., Lin, C., Grauman, K., Luo, J., and Bigham, J. P. Vizwiz grand challenge: Answering visual questions from blind people. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 3608–3617, 2018.

Hu, E. J., Shen, Y., Wallis, P., Allen-Zhu, Z., Li, Y., Wang, S., Wang, L., and Chen, W. Lora: Low-rank adaptation of large language models. *arXiv preprint arXiv:2106.09685*, 2021.

Huang, S., Dong, L., Wang, W., Hao, Y., Singhal, S., Ma, S., Lv, T., Cui, L., Mohammed, O. K., Liu, Q., et al. Language is not all you need: Aligning perception with language models. *arXiv preprint arXiv:2302.14045*, 2023.

Hudson, D. A. and Manning, C. D. Gqa: A new dataset for real-world visual reasoning and compositional question answering. In *Proceedings of the IEEE/CVF conference* *on computer vision and pattern recognition*, pp. 6700–6709, 2019.

Iyer, S., Lin, X. V., Pasunuru, R., Mihaylov, T., Simig, D., Yu, P., Shuster, K., Wang, T., Liu, Q., Koura, P. S., et al. Opt-iml: Scaling language model instruction meta learning through the lens of generalization. *arXiv preprint arXiv:2212.12017*, 2022.

Kafle, K. and Kanan, C. An analysis of visual question answering algorithms. In *Proceedings of the IEEE international conference on computer vision*, pp. 1965–1973, 2017.

Kazemzadeh, S., Ordonez, V., Matten, M., and Berg, T. Referitgame: Referring to objects in photographs of natural scenes. In *Proceedings of the 2014 conference on empirical methods in natural language processing (EMNLP)*, pp. 787–798, 2014.

Kiela, D., Firooz, H., Mohan, A., Goswami, V., Singh, A., Ringshia, P., and Testuggine, D. The hateful memes challenge: Detecting hate speech in multimodal memes. *Advances in neural information processing systems*, 33: 2611–2624, 2020.

Krishna, R., Zhu, Y., Groth, O., Johnson, J., Hata, K., Kravitz, J., Chen, S., Kalantidis, Y., Li, L.-J., Shamma, D. A., et al. Visual genome: Connecting language and vision using crowdsourced dense image annotations. *International journal of computer vision*, 123:32–73, 2017.

Laurençon, H., Saulnier, L., Tronchon, L., Bekman, S., Singh, A., Lozhkov, A., Wang, T., Karamcheti, S., Rush, A. M., Kiela, D., et al. Obelisc: An open web-scale filtered dataset of interleaved image-text documents. *arXiv preprint arXiv:2306.16527*, 2023.

Li, B., Wang, R., Wang, G., Ge, Y., Ge, Y., and Shan, Y. Seed-bench: Benchmarking multimodal llms with generative comprehension. *arXiv preprint arXiv:2307.16125*, 2023a.

Li, B., Zhang, Y., Chen, L., Wang, J., Pu, F., Yang, J., Li, C., and Liu, Z. Mimic-it: Multi-modal in-context instruction tuning. *arXiv preprint arXiv:2306.05425*, 2023b.

Li, B., Zhang, Y., Chen, L., Wang, J., Yang, J., and Liu, Z. Otter: A multi-modal model with in-context instruction tuning. *arXiv preprint arXiv:2305.03726*, 2023c.

Li, G., Hammoud, H. A. A. K., Itani, H., Khizbullin, D., and Ghanem, B. Camel: Communicative agents for "mind" exploration of large scale language model society, 2023d.

Li, L., Peng, J., Chen, H., Gao, C., and Yang, X. How to configure good in-context sequence for visual question answering. *arXiv preprint arXiv:2312.01571*, 2023e.

Liang, S., Zhu, K., Tian, R., Qin, Y., Wang, H., Cong, X., Liu, Z., Liu, X., and Sun, M. Exploring format consistency for instruction tuning. *arXiv preprint arXiv:2307.15504*, 2023.

Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., Dollár, P., and Zitnick, C. L. Microsoft coco: Common objects in context. In *Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part V 13*, pp. 740–755. Springer, 2014.

Liu, F., Emerson, G., and Collier, N. Visual spatial reasoning. *Transactions of the Association for Computational Linguistics*, 11:635–651, 2023a.

Liu, H., Li, C., Wu, Q., and Lee, Y. J. Visual instruction tuning. *arXiv preprint arXiv:2304.08485*, 2023b.

Liu, J., Wang, L., and Yang, M.-H. Referring expression generation and comprehension via attributes. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 4856–4864, 2017.

Loshchilov, I. and Hutter, F. Decoupled weight decay regularization. In *International Conference on Learning Representations*, 2018.

Mao, J., Huang, J., Toshev, A., Camburu, O., Yuille, A. L., and Murphy, K. Generation and comprehension of unambiguous object descriptions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 11–20, 2016.

Marino, K., Rastegari, M., Farhadi, A., and Mottaghi, R. Ok-vqa: A visual question answering benchmark requiring external knowledge. In *Proceedings of the IEEE/cvf conference on computer vision and pattern recognition*, pp. 3195–3204, 2019.

Mishra, A., Shekhar, S., Singh, A. K., and Chakraborty, A. Ocr-vqa: Visual question answering by reading text in images. In *2019 international conference on document analysis and recognition (ICDAR)*, pp. 947–952. IEEE, 2019.

OpenAI. Gpt-4 technical report, 2023.

Peng, Y., Yang, X., Ma, H., Xu, S., Zhang, C., Han, Y., and Zhang, H. Icd-lm: Configuring vision-language in-context demonstrations by language modeling. *arXiv preprint arXiv:2312.10104*, 2023.

Radford, A., Kim, J. W., Hallacy, C., Ramesh, A., Goh, G., Agarwal, S., Sastry, G., Askell, A., Mishkin, P., Clark, J., et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pp. 8748–8763. PMLR, 2021.

Rasley, J., Rajbhandari, S., Ruwase, O., and He, Y. Deepspeed: System optimizations enable training deep learning models with over 100 billion parameters. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pp. 3505–3506, 2020.

Reddy, S., Chen, D., and Manning, C. D. CoQA: A conversational question answering challenge. *Transactions of the Association for Computational Linguistics*, 7:249–266, 2019. doi: 10.1162/tacl_a_00266. URL https://aclanthology.org/Q19-1016.

Suhr, A., Lewis, M., Yeh, J., and Artzi, Y. A corpus of natural language for visual reasoning. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pp. 217–223, 2017.

Sun, Q., Yu, Q., Cui, Y., Zhang, F., Zhang, X., Wang, Y., Gao, H., Liu, J., Huang, T., and Wang, X. Generative pretraining in multimodality. *arXiv preprint arXiv:2307.05222*, 2023.

Tai, Y., Fan, W., Zhang, Z., Zhu, F., Zhao, R., and Liu, Z. Link-context learning for multimodal llms. *arXiv preprint arXiv:2308.07891*, 2023.

Taori, R., Gulrajani, I., Zhang, T., Dubois, Y., Li, X., Guestrin, C., Liang, P., and Hashimoto, T. B. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford_alpaca, 2023.

Team, M. N. Introducing mpt-7b: A new standard for open-source, commercially usable llms, 2023. URL www.mosaicml.com/blog/mpt-7b. Accessed: 2023-05-05.

Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.-A., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.

Veit, A., Matera, T., Neumann, L., Matas, J., and Belongie, S. Coco-text: Dataset and benchmark for text detection and recognition in natural images. *arXiv preprint arXiv:1601.07140*, 2016.

Xu, Z., Shen, Y., and Huang, L. Multiinstruct: Improving multi-modal zero-shot learning via instruction tuning. In *Annual Meeting of the Association for Computational Linguistics*, 2022.

Yang, X., Wu, Y., Yang, M., and Chen, H. Exploring diverse in-context configurations for image captioning. *arXiv preprint arXiv:2305.14800*, 2023.

Yang, Z., Gan, Z., Wang, J., Hu, X., Lu, Y., Liu, Z., and Wang, L. An empirical study of gpt-3 for few-shot knowledge-based vqa. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 36, pp. 3081–3089, 2022.

Young, P., Lai, A., Hodosh, M., and Hockenmaier, J. From image descriptions to visual denotations: New similarity metrics for semantic inference over event descriptions. *Transactions of the Association for Computational Linguistics*, 2:67–78, 2014.

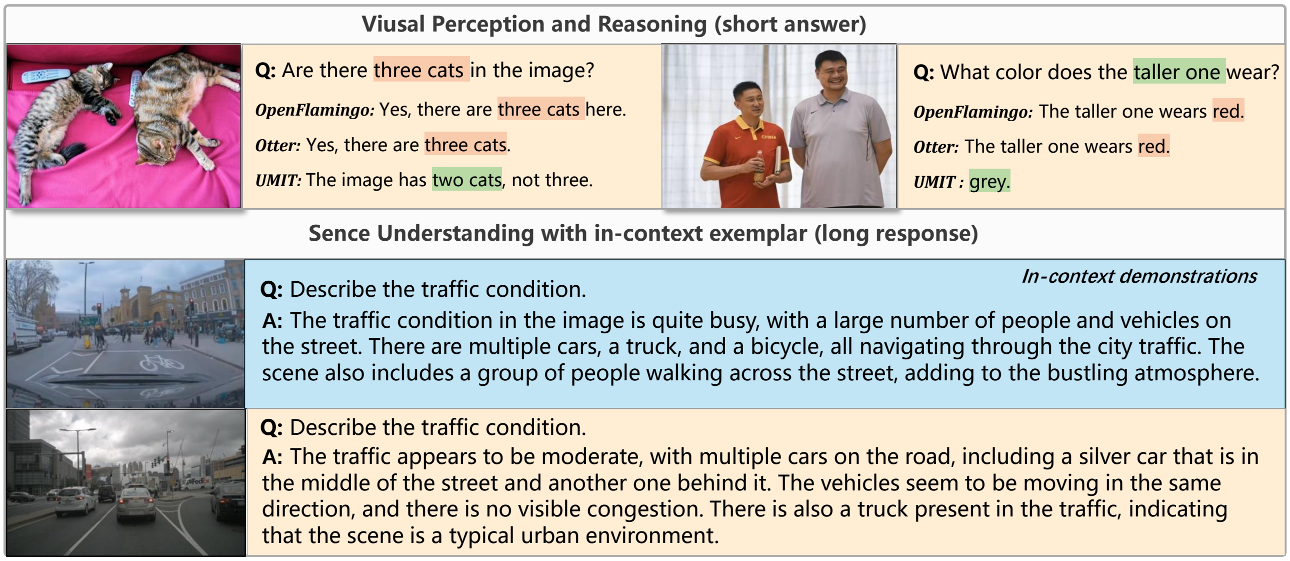
Zhao, B., Wu, B., and Huang, T. Svit: Scaling up visual instruction tuning. *arXiv preprint arXiv:2307.04087*, 2023a.

Zhao, H., Cai, Z., Si, S., Ma, X., An, K., Chen, L., Liu, Z., Wang, S., Han, W., and Chang, B. Mmicl: Empowering vision-language model with multi-modal in-context learning. *arXiv preprint arXiv:2309.07915*, 2023b.

Zhou, Y., Wang, M., Liu, D., Hu, Z., and Zhang, H. More grounded image captioning by distilling image-text matching model. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 4777–4786, 2020.

Zhu, D., Chen, J., Shen, X., Li, X., and Elhoseiny, M. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *arXiv preprint arXiv:2304.10592*, 2023.

Zhu, Y., Groth, O., Bernstein, M., and Fei-Fei, L. Visual7w: Grounded question answering in images. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4995–5004, 2016.


Viusal Perception and Reasoning (short answer)
Sence Understanding with in-context exemplar (long response)
In-context demonstrations

Q: Are there three cats in the image?

OpenFlamingo: Yes, there are three cats here.

Otter: Yes, there are three cats.

UMIT: The image has two cats, not three.

Q: What color does the taller one wear?

OpenFlamingo: The taller one wears red.

Otter: The taller one wears red.

UMIT : grey.

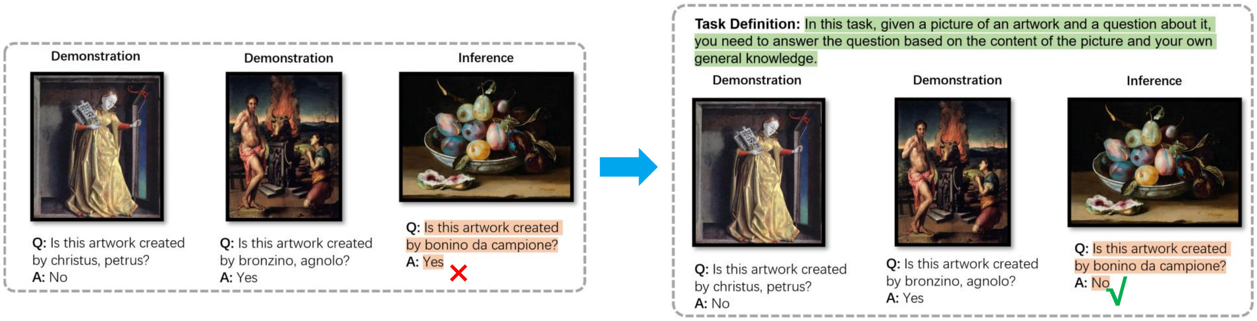
Q: Describe the traffic condition.

A: The traffic condition in the image is quite busy, with a large number of people and vehicles on the street. There are multiple cars, a truck, and a bicycle, all navigating through the city traffic. The scene also includes a group of people walking across the street, adding to the bustling atmosphere.

Q: Describe the traffic condition.

A: The traffic appears to be moderate, with multiple cars on the road, including a silver car that is in the middle of the street and another one behind it. The vehicles seem to be moving in the same direction, and there is no visible congestion. There is also a truck present in the traffic, indicating that the scene is a typical urban environment.

Figure 4: Examples illustrate that our model can avoid being misled in traditional vision-language tasks (short answers) while also demonstrating improved position awareness for visual reasoning. Additionally, our model can learn from exemplars to generate long responses (human preferences).



Q: Is this artwork created by christus, petrus?
A: No

Q: Is this artwork created by bronzino, agnolo?
A: Yes

Q: Is this artwork created by bonino da campione?
A: Yes ✗

Task Definition: In this task, given a picture of an artwork and a question about it, you need to answer the question based on the content of the picture and your own general knowledge.

Q: Is this artwork created by christus, petrus?
A: No

Q: Is this artwork created by bronzino, agnolo?
A: Yes

Q: Is this artwork created by bonino da campione?
A: No ✓

Figure 5: This example illustrates that by incorporating task definition, the model can learn to understand in-context exemplars, thereby enhancing in-context learning ability.

A. Vision-Language Task Collection

Previous works have demonstrated that extending visual instruction datasets can improve performance on unseen tasks with different multimodal instruction formats (Xu et al., 2022; Dai et al., 2023; Li et al., 2023c; Zhao et al., 2023b), as shown in Table 1. Therefore, we select 55 tasks from these datasets and merge them into a unified multimodal instruction format for training and evaluation.

A.1. Dataset Resource

Image Caption (IC) The aim of this type of image caption task is to evaluate the model's overall perception of images, which is the foundation of all vision-language tasks. For example, we include MSCOCO (Lin et al., 2014) and Flickr30K (Young et al., 2014) datasets for short image descriptions, but LLaVA-Instruct-23k (Liu et al., 2023b) and SVIT (Zhao et al., 2023a) datasets for detailed image descriptions.

Visual Question Answering (VQA) The majority of vision-language tasks can be generally viewed as Visual Question Answering (VQA) tasks, requiring the model to provide answers to queries related to the image. Therefore, we collect 17 VQA tasks from diverse datasets, such as VQAv2 (Goyal et al., 2017), OK-VQA (Marino et al., 2019), GQA (Hudson

Dataset	IC	VQA	VR	RD	Text	Few-Shot	# Tasks	# Exs
LLaVA†	✔	✔	✔	✗	✗	✗	3	158k
MiniGPT-4†	✔	✗	✗	✗	✗	✗	N/A	3.5k
Otter	✔	✔	✔	✗	✗	✔	47	$\sim$ 2.8M
MultiModal-GPT	✔	✔	✔	✗	✔	✗	7	$\sim$ 164k
InstructBLIP	✔	✔	✔	✗	✗	✗	13	$\sim$ 1.6M
M^{3}IT	✔	✔	✔	✔	✗	✗	40	2.4M
Clever Flamingo†	✔	✔	✔	✔	✗	✗	37	975k
Shikra†	✔	✔	✔	✔	✗	✗	4	$\sim$ 90k
Emu†	✔	✔	✔	✗	✔	✗	4	$\sim$ 282k
`UMIT`†	✔	✔	✔	✔	✔	✔	55	148k

Table 7: Summary of visual instruction tuning datasets used by existing models. † indicates that the model is trained in two stages.

& Manning, 2019), OCR-VQA (Mishra et al., 2019), and TDIUC (Kafle & Kanan, 2017), among others.

Visual Reasoning (VR) This category of task serves to assess the model's proficiency in visual reasoning. Specifically, we include some reasoning tasks: RD data generated by Chen et al. (2023b), Visual Reasoning in Natural Language (Suhr et al., 2017), Visual Spatial Reasoning (Liu et al., 2023a) for spatial reasoning, LLaVA-Instruct-77K and SVIT, both generated by GPT-4 (OpenAI, 2023), for complex reasoning.

Visual Dialog (VR) This task necessitates the model's capacity to chat naturally with humans about visual content. We include visual dialogue (Das et al., 2017), LLaVA-Instruct-58k and SVIT.

Referential Dialogue (RD) This type of task is defined by Shikra (Chen et al., 2023b), which covers a wide range of vision-language positioning tasks for fine-grained image comprehension, including tasks: referring expression comprehension (REC) (Kazemzadeh et al., 2014; Mao et al., 2016), VQA grounding and grounding caption (GC) (Zhou et al., 2020), referring expression generation (REG) (Liu et al., 2017). Additionally, we also propose the Referential Complex Reasoning (RCR) task and Referential Detailed Description (RDD) task based on the SVIT datasets by employing ChatGPT to add objects' bounding boxes to their responses.

Language-only tasks To maintain the chatting and text instruction-following capabilities of language models, we include tasks: Alpaca GPT-4 (Taori et al., 2023), Dolly 15k (Conover et al., 2023). For learning to reason, Flan-mini CoT (Ghosal et al., 2023), CodeX MathQA, CoQA (Reddy et al., 2019), Math (Li et al., 2023d) datasets are also incorporated. Note that we filter out some out-of-domain examples to avoid language models learning to refuse to answer image-related instructions.

A.2. Comparison of Existing Visual Instruction Tuning Datasets

Currently, there are many novel models in visual instruction tuning, most of which are data-centric studies. Therefore, we summarize the datasets employed by the part of multimodal large language models (MLLMs) and compare them with those used by `UMIT`, shown in Table 7. Notably, the training process of many MLLMs consists of two stages (indicated by †), and we generally consider that the first stage is employed for aligning their visual and textual features, while the second stage is truly for visual instruction tuning. Therefore, we only consider the training data from the second stage for these models.

LLaVA utilizes the COCO dataset, leveraging its caption and object bounding box information, to prompt GPT-4 in generating 158k high-quality visual instruction data. These instructions are categorized into three types: detailed descriptions, conversations, and complex reasoning.

MiniGPT-4 employs ChatGPT to paraphrase 5,000 image descriptions generated by raw MiniGPT-4 (trained in the first stage), and manually selected 3,500 high-quality image caption data from them.

Otter proposes a dataset named MIMIC-IT, consisting of 47 different tasks, to enable the model to follow user instructions while preserving the in-context learning capability of OpenFlamingo. Each sample within the dataset contains few-shot templates for in-context instruction tuning. Additionally, MIMIC-IT serves as a multilingual visual instruction dataset.

MultiModal-GPT integrates datasets from LLaVA and MiniGPT-4, along with several traditional vision-language tasks, including A-OKVQA, COCO Caption, and OCR VQA. To maintain the model's ability to chat with humans, it also introduces language-only tasks, including Dolly 15k and the GPT-4 alpaca dataset.

InstructBLIP also employs the LLaVA dataset, but it's more focused on traditional vision-language tasks, aiming to improve its generalization performance to unseen tasks by increasing task diversity. In total, this work collects 26 vision-language tasks, with half of them used for training and the other half for evaluation.

M³IT assembles 40 traditional vision-language datasets, and it also belongs to a multilingual visual instruction dataset, spanning over 80 languages. Despite encompassing such a multitude of datasets, each one only contains a single task, thereby constraining its task diversity.

Clever Flamingo collects 37 vision-language tasks and utilizes the Polite Flamingo model (trained in the first stage) to rewrite the answers of these tasks into human-preferred responses, resulting in a high-quality PF-1M dataset that assists the model in reducing multimodal tax.

Shikra focuses on referential dialogue. It utilizes GPT-4 to generate 7,800 high-quality location-related question pairs which are considered as the Grounding Chain-of-Thought (GCoT) data based on the Flickr30K dataset. Additionally, it also incorporates 50% of the LLaVA dataset. As a result, there are a total of four types of tasks included.

Emu is trained to align with users' intentions and generalize to unseen tasks through visual instruction tuning, which gathers tasks from three distinct modalities: text, image, and video. For language-only tasks, the ShareGPT and Alpaca datasets are utilized. The LLaVA dataset is employed to align with image instructions, and the VideoChat dataset is introduced to assist the model in understanding video instructions.

A.3. Prompt Templates Statistics

Data Filtering Strategy. Using natural language to describe position information would significantly occupy the prompt length. Considering the most extreme scenario, we need to incorporate in-context exemplars responses, leading to excessive prompt length for certain examples. Therefore, we filter out these examples. Additionally, for language-only tasks, we exclude examples containing words or phrases like "image" and "I'm sorry," aiming to prevent our model from hallucination and learning to refuse instructions related to images. Finally, this filtering process reduces our actual training examples from 148,304 to 121,184.

In-context Exemplars. We utilize the approach described in Section 3.4 to select in-context exemplars for examples in vision-language tasks. In practice, we set k to 3, meaning that for each example, we select 6 in-context exemplars (3 image exemplars and 3 text exemplars) based on cosine similarity. Each exemplar cosine similarity must surpass a certain threshold to be considered, with thresholds of 0.7 and 0.8 for image and text exemplars, respectively. For some tasks, such as NLP tasks, we randomly select in-context exemplars that are not counted in the final few-shot template quantity.

Table 8: Exemplars with different types of prompts, including CoT and few-shot templates.

	#Samples	**Pct. (%)**
Total samples	155,304	100.00%
Filtered samples	148,304	95.49%
Few-shot templates	51,513	33.17%
Few-shot templates (image)	24,945	16.06%
Few-shot templates (text)	26,568	17.11%

B. Evaluation Metrics

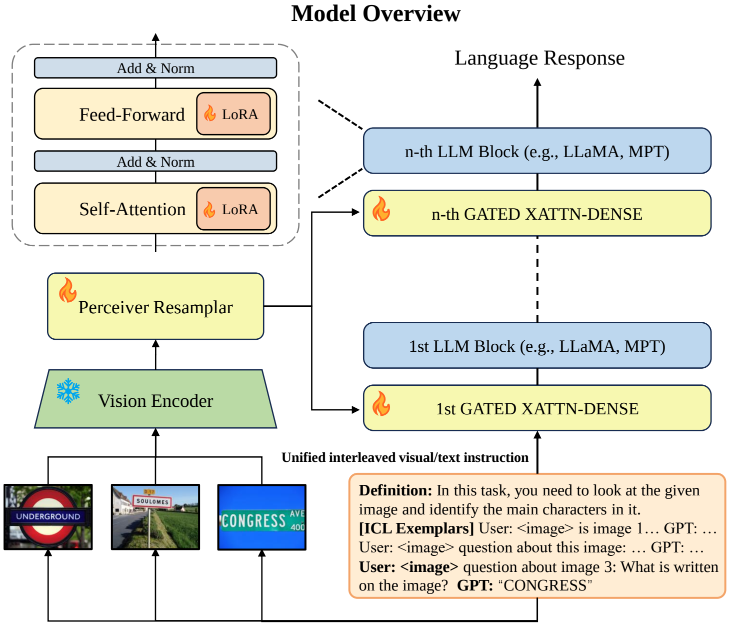
We provide evaluation metrics as Table 9. For the Flickr30K dataset, we report the CIDEr score to assess model performance using the coco-caption evaluation code [3]. Regarding ScienceQA, following Dai et al. (2023), we remove samples without images and employ standard evaluation code [4] to calculate top-1 accuracy (%). It's important to note that for all tasks, we refrain from adding vocabulary constraints and rankings approaches.

[3] https://github.com/tylin/coco-caption

[4] https://github.com/lupantech/ScienceQA

Dataset	Task	Split	Samples	Metric
Flickr30K	Scene description	Test	1000	CIDEr(↑)
OK-VQA	Knowledge Grounded VQA	Val	5046	VQA acc.(↑)
TextVQA	Reading Comprehension VQA	Val	5000	VQA acc.(↑)
ScienceQA	Visual Reasoning QA	Test	2017	Accuracy(↑)
HatefulMemes	Image Classification	Test	1000	ROC-AUC(↑)
VizWiz	Scene Perception	Val	4319	VQA acc.(↑)
ISEKAI	Link-Context Learning	Test	1256	Accuracy(↑)

Table 9: Description of dataset in zero- and few-shot evaluation benchmarks.



Definition: In this task, you need to look at the given image and identify the main characters in it.
[ICL Exemplars] User: <image> is image 1… GPT: …
User: <image> question about this image: … GPT: …
User: <image> question about image 3: What is written on the image? **GPT:** "CONGRESS"

Figure 6: Our model overview.

C. Model

Architecture. Our model is based on OpenFlamingo architecture. The model consists of a vision encoder from CLIP (Radford et al., 2021), a perceiver resampler to receive the visual features from the vision encoder, and a text encoder from large language models (e.g., LLaMA (Touvron et al., 2023), MPT (Team, 2023)) equipped with gated cross-attention layers for image-text interactions. To preserve the pretraining knowledge and reduce computing consumption, We freeze both the encoders and only finetune the perceiver resampler module, gated cross-attention layers, and LoRA (Hu et al., 2021) module added to the text encoder, as shown in Figure 6.

Training Details. Our model is trained in two stages. The first stage aims to facilitate the model's capability to comprehend numerical positional coordinates in natural language. We train `UMIT` for 2 epochs (approximately 10k steps), using several datasets encompassing RefCOCO for REC and REG tasks, Visual Genome for GC tasks, and our newly introduced RDD and RCR tasks (Appendix A.1). In the second stage, we train `UMIT` on our proposed dataset with only 155k samples but consisting of 55 tasks in `DEIQA` format ($\mathcal{F}_3$). It takes around 30h for stage one training and 6h for stage two.

Training Strategy for In-Context Learning. After retrieval, every example from most tasks has $2k$ in-context exemplars to construct the unified multimodal instruction format. However, adding in-context exemplars can significantly increase the length of the prompt, leading to sparsity in the loss and lower batch diversity. Therefore, we follow Iyer et al. (2022) to in-context instruction-finetune our model with suffix loss rather than the original MetaICL loss, as illustrated in Table 10.

```
Definition: [Task Definition (task-level instruction)]
# in-context exemplars
User: <image>question about image 1:[question]
GPT: <answer> [answer] <endofchunk>
...
User: <image> question about image 3:[question]
GPT: <answer> [answer] <endofchunk>
# current instance
User: <image> question about this image:[question]
GPT: <answer> [answer] <endofchunk>
```

Table 10: `<image>` and `<endofchunk>` tokens are originally from the OpenFlamingo training paradigm, and we follow Li et al. (2023c) to include a new token `<answer>` for intercepting the target answer of the model output more easily, which can also assist in adjusting in-context learning loss mentioned in Appendix A.3. Note that only green sequence/tokens are used to compute the loss and we train our model using a cross-entropy loss and .

The difference between the two is that the former only calculates the loss of the last target answer, while the latter needs to calculate the loss from the first exemplars' answer and the remaining part, which mitigates the problem of loss sparsity.

D. Task Definition

Task definitions generated by GPT-3.5 for MME Benchmark, as shown in Table 9.

- **Existence**: In this task, you will receive an image and a question about the existence of an object in the image.
- **Count**: In this task, you will need to compare the number of objects in a given image with the sentence given, and determine whether the number is correct or not.
- **Position**: In this task, you are given a sentence and a image. You need to judge whether the sentence correctly describes the positional relationships between objects in the diagram.
- **Color**: In this task, you need to look at the given image and answer whether the color described in the question matches the content of the image.
- **Posters**: In this task, you need to determine if the description of the given question matches the information of a poster image.
- **Celebrity**: In this task, you will receive an image and a question about the name of the celebrity selected by a red bounding box in this image.
- **Scene**: In this task, you need to look at the image and determine whether the description of the image in the given question is correct or not.
- **Landmark**: In this task, you need to evaluate whether the given question is correctly describing the name of the landmark in the image.
- **Artwork**: In this task, given a picture of an artwork and a question about it, you need to answer the question based on the content of the picture and your own general knowledge.
- **OCR**: In this task, you need to evaluate whether the characters mentioned in a sentence are the same as the ones in a given image.

Table 11: The list of task definitions for MME Benchmark.

Task definitions generated by GPT-3.5 for SEED-Bench, as shown in Table 12.

- **Scene Understanding**: In this task, you need to analyze the scene in the provided image and answer a given question.
- **Instance Identity**: In this task, you will receive an image and please answer a question about the existence of some objects in the image.
- **Instance Attributes**: In this task, you need to answer questions about the attribute of an object in the following images.
- **Instance Location**: In this task, you are required to understand the location of objects in the image and answer a question about this location information in the image.
- **Instance Counting**: In this task, you need to count the number of objects in this image and answer the corresponding question.
- **Spatial Relations**: In this task, you need to answer a question by understanding the spatial relations between objects in a given image.
- **Instance Interaction**: In this task, you need to find two objects in a given image and then reason out their relation by looking at the image to answer a question.
- **Visual Reasoning**: In this task, you need to answer the given questions by referring to the content of the image and using commonsense reasoning.
- **Text Recognition**: In this task, you are given an image with some texts on it and you need to locate the texts in the image and answer a corresponding question related to them.

Table 12: The list of task definitions for SEED-Bench.

Table 13: Detailed information of visual instruction tuning dataset we collected.

Dataset	Task Name	#samples		Source
		Train	Valid	
MSCOCO (Lin et al., 2014)	Image Caption	2,000	200	MSCOCO
	Question-Image Matching	2,000	200	MultiInstruct
	Image-Text Selection	2,000	200	MultiInstruct
	Image-Text Matching	2,000	200	MultiInstruct
	Object Grounding	2,000	200	MultiInstruct
	Object-Region Matching	2,000	200	MultiInstruct
	Object-Region Selection	2,000	200	MultiInstruct
	Object Matching	2,000	200	MultiInstruct
	Missing Object Selection	2,000	200	MultiInstruct
IQA (Duanmu et al., 2021)	Image Quality	2,000	200	IQA
COCO-Text (Veit et al., 2016)	Text Type Classification	2,000	200	COCO-Text
	Text Legibility	2,000	200	COCO-Text
	Region-Text Matching	2,000	200	COCO-Text
	Text Localization	2,000	200	COCO-Text
Visual Genome (Krishna et al., 2017)	Grounded Captioning	2,000	200	Visual Genome
	Visual Grounding	2,000	200	Visual Genome
	Most-Overlapping Region Selection	2,000	200	MultiInstruct
	Non-Overlapping Region Selection	2,000	200	MultiInstruct
	Least-Overlapping Region Selection	2,000	200	MultiInstruct
	Overlapping Region Selection	2,000	200	MultiInstruct
	Region Overlapping Detection	2,000	200	MultiInstruct
	Region-Caption Matching	2,000	200	MultiInstruct
	Grounded Caption Selection	2,000	200	MultiInstruct
	Visual Grounding Selection	2,000	200	MultiInstruct
RefCOCO (Kazemzadeh et al., 2014)	Referring Expression Selection	6,000	200	MultiInstruct
RefCOCO+	Referring Expression Generation	6,000	200	RefCOCO
RefCOCOg	Referring Expression Comprehension	6,000	200	RefCOCO
Visual7w (Zhu et al., 2016)	Grounded VQA	2,000	200	Visual7w
GQA (Hudson & Manning, 2019)	Visual Reasoning	2,000	200	GQA
OCR VQA (Mishra et al., 2019)	Reading Comprehension VQA	2,000	200	OCR VQA
OK-VQA (Marino et al., 2019)	Knowledge Grounded VQA	2,000	200	OK-VQA
VQAv2 (Goyal et al., 2017)	Open-Domain VQA	2,000	200	VQAv2
TDIUC (Kafle & Kanan, 2017)	Sport Recognition	2,000	200	TDIUC
	Scene Recognition	2,000	200	TDIUC
	Color Attribute	2,000	200	TDIUC
	Other Attribute	2,000	200	TDIUC
	Activity Recognition	2,000	200	TDIUC
	Position Reasoning	2,000	200	TDIUC
	Object Recognition	2,000	200	TDIUC
	Absurd	2,000	200	TDIUC
	Utility and Affordance	291	143	TDIUC
	Object Presence	2,000	200	TDIUC
	Counting	2,000	200	TDIUC
	Sentiment	1,242	200	TDIUC
LLaVA-Instruct (Liu et al., 2023b)	Detailed Description	3,500	-	LLaVA
SVIT-Instruct (Zhao et al., 2023a)	Complex Reasoning	3,500	-	LLaVA
	Conversation	7,000	-	LLaVA
Otter-LA-I (Li et al., 2023b)	LLaVA-Interleaved	7,000	-	Otter
Shikra-RD (Chen et al., 2023b)	Referential Dialogue	7,800	-	Shikra
GQA-CoT	Referential Dialogue GCoT	5,000	-	Shikra
Ours	Referential Detailed Description	5,000	-	Ours
(Generated data from SVIT)	Referential Complex Reasoning	3,971	-	Ours
Alpaca (Taori et al., 2023) Dolly (Conover et al., 2023)	Human Preferred Text Instruction	4,000	-	Alpaca
MathQA (Amini et al., 2019)	CodeX Math QA	2,000	-	-
Flan-Mini (Ghosal et al., 2023)	Flan-CoT	2,000	-	Flan
CoQA (Reddy et al., 2019)	Conversational QA	5,000	-	CoQA
Math (Li et al., 2023d)	Math	2,000	-	Camel-AI