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Large Multimodal Models:
Notes on CVPR 2023 Tutorial

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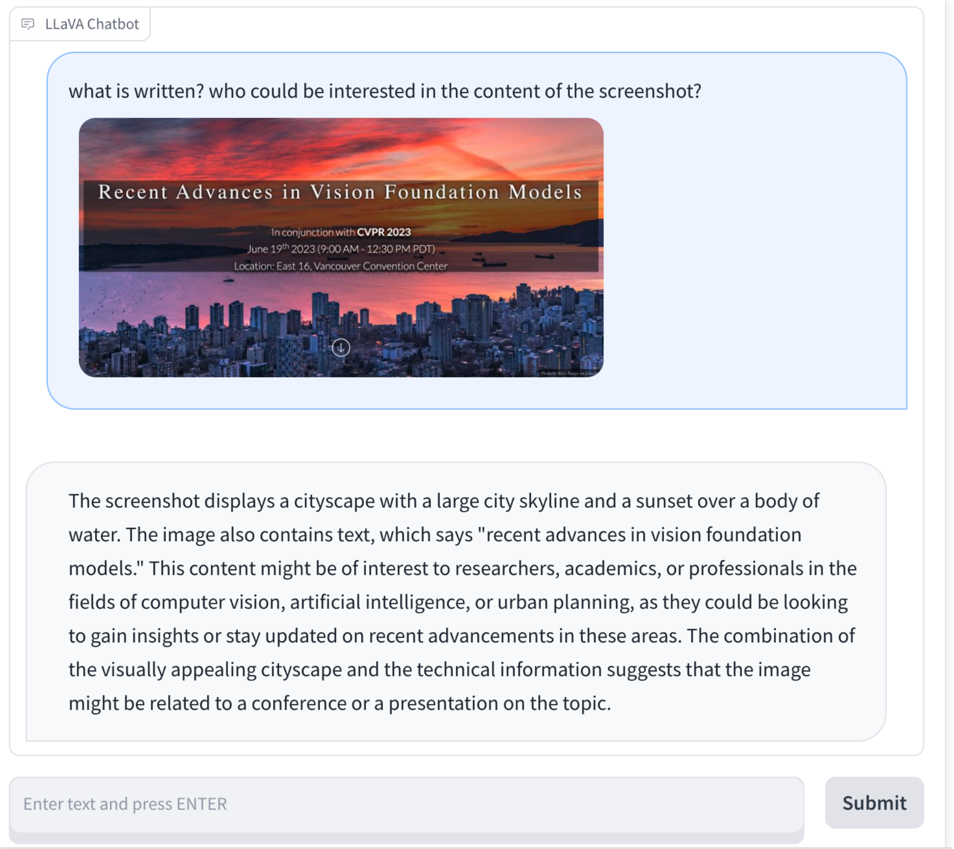
Abstract

This tutorial note summarizes the presentation on *Large Multimodal Models: Towards Building and Surpassing Multimodal GPT-4*, a part of CVPR 2023 tutorial on *Recent Advances in Vision Foundation Models*. The tutorial consists of three parts. We first introduce the background on recent GPT-like large models for vision-and-language modeling to motivate the research in instruction-tuned large multimodal models (LMMs). As a pre-requisite, we describe the basics of instruction-tuning in large language models, which is further extended to the multimodal space. Lastly, we illustrate how to build the minimum prototype of multimodal GPT-4 like models with the open-source resource, and review the recently emerged topics.


LLaVA Chatbot
Recent Advances in Vision Foundation Models
In conjunction with CVPR 2023
June 19th 2023 (9:00 AM - 12:30 PM PDT)
Location: East 16, Vancouver Convention Center
Enter text and press ENTER
Submit

what is written? who could be interested in the content of the screenshot?

The screenshot displays a cityscape with a large city skyline and a sunset over a body of water. The image also contains text, which says "recent advances in vision foundation models." This content might be of interest to researchers, academics, or professionals in the fields of computer vision, artificial intelligence, or urban planning, as they could be looking to gain insights or stay updated on recent advancements in these areas. The combination of the visually appealing cityscape and the technical information suggests that the image might be related to a conference or a presentation on the topic.

Figure 1: Visual chat with LMM. Generated by LLaVA: https://llava-vl.github.io/

Preprint. Tutorial Notes.

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1 Prologue

In view of the rapid assimilation and widespread adoption of OpenAI ChatGPT [32]/GPT-4 [33] in contemporary society, there has been a growing interest among academics and researchers to develop open-source large language models (LLMs), and simultaneously explore the extensions into large multimodal models (LMMs)[1]. In order to elucidate this popular topic for a broader audience, in the CVPR 2023 tutorial on *Recent Advances in Vision Foundation Models*, we have provided a lecture on *Large Multimodal Models: Towards Building and Surpassing Multimodal GPT-4*, based on the public materials in the literature. This note summarizes the tutorial presentation and makes it more complete. It gives guided tours through the literature and explain topics to those who seek to learn the areas on LMMs from basics to the advances. It is prepared for audience including graduate students, researchers and professionals that LMMs are outside their specialties, to help them develop perspectives, and identify trends in LMMs in an accessible way.

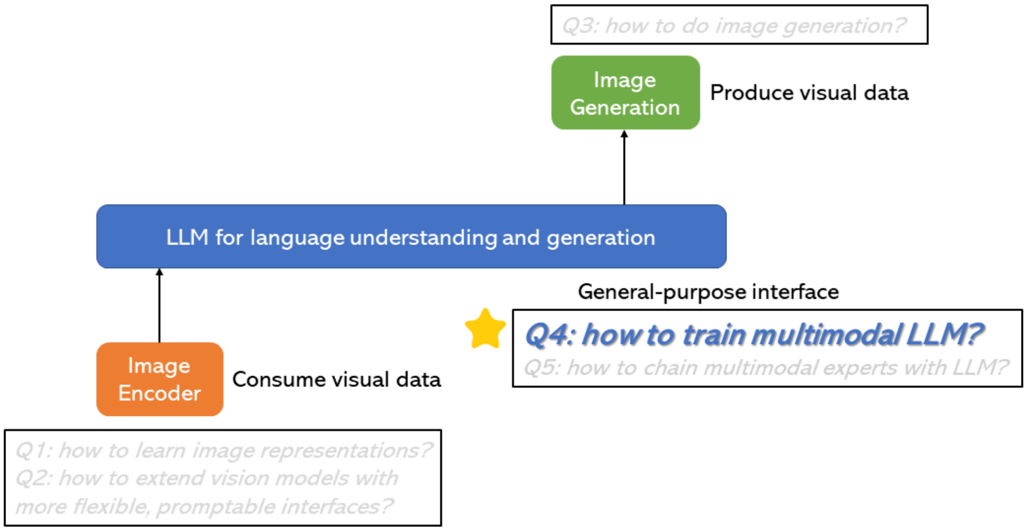
Q3: how to do image generation?
Image Generation
Produce visual data
LLM for language understanding and generation
General-purpose interface
Q4: how to train multimodal LLM?
Q5: how to chain multimodal experts with LLM?
Image Encoder
Consume visual data
Q1: how to learn image representations?
Q2: how to extend vision models with more flexible, promptable interfaces?

Figure 2: The focus of this note on large multimodal models, in the context of overall CVPR 2023 Tutorial on *Recent Advances in Vision Foundation Models*.

In the full tutorial, as shown in Figure 2, we have covered the most recent approaches and principles at the frontier of learning and applying vision foundation models, including Q1: Visual and Vision-Language Pre-training; Q2: Generic Vision Interface; Q3: Alignments in Text-to-image Generation; Q4: Large Multimodal Models; and Q5: Multimodal Agents.

This note focuses on Q4: how to leverage LLM for multimodality, and train LMMs in an end-to-end fashion, so that the models can see and chat. The presentation consists of three parts. To start, we first share background on recent GPT-like large models for vision-and-language modeling in Section 2. In the 2nd part, as a pre-requisite, we will introduce the concept of instruction tuning in language domains in Section 3, which empowered ChatGPT. Finally, Section 4 covers the last part of the presentation, where we focus on how to build a minimum version of multimodal GPT-4, using LLaVA as a running example. Since LMM is a popular research topic, many new papers have appeared in this line of research in the past three months, of which we provide a summary, so that the audience may quickly get a picture on what the LMM community has been working on.

The related links of the tutorial presentation on large multimodal models are available at:

- *Slides*: `https://tinyurl.com/5c2c2mtm`
- *YouTube Video*: `https://youtu.be/mkI7EPD1vp8`
- *Bilibili Video*: `https://www.bilibili.com/video/BV1Ng4y1T7v3/`

For the full information and other parts of the CVPR tutorial, please see the official website at:

`https://vlp-tutorial.github.io/`

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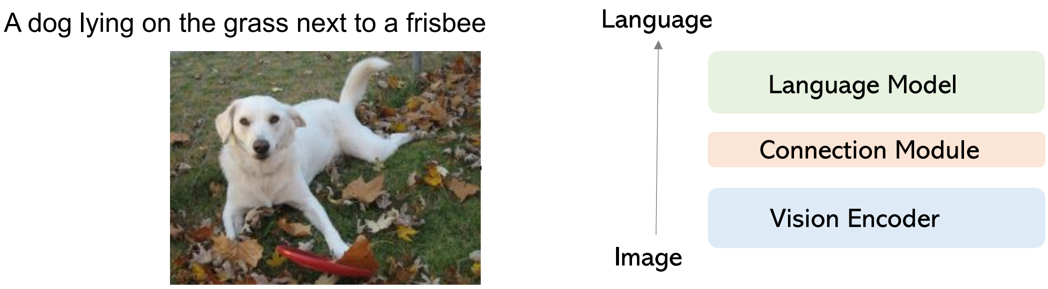
[1] Within this manuscript, we will utilize the terms *LMM* and *multimodal LLM* interchangeably.

2 Background

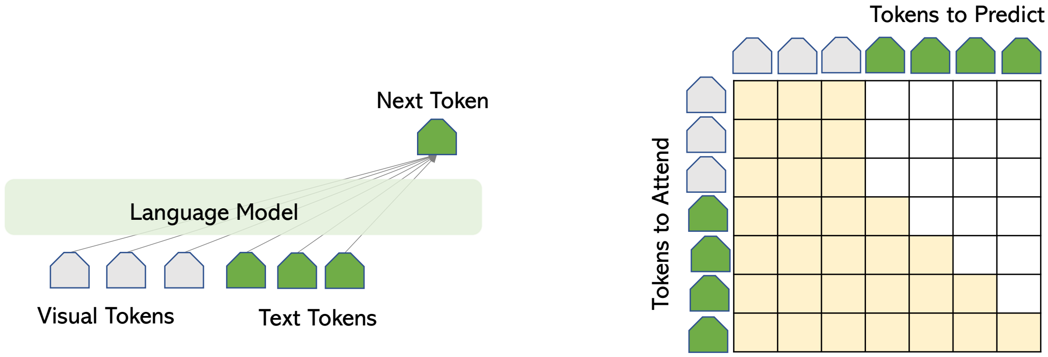
2.1 Image-to-Text Generative Models

LMMs in their current form is primarily an image-to-text generative model, which takes images as input, and outputs a text sequence. One example is illustrated in Figure 3 (a) Left. All of the model variants share very similar model architecture and training objective.

- *Model Architecture*. As illustrated in Figure 3 (a) Right, the model typically consists of an image encoder to extract visual features, and a language model to decode the text sequence. The vision and language modalities can be optionally connected by trainable connection module. The image encoder and language model can be either trained from scratch or initialized from pre-trained models.
- *Training Objective*. As illustrated in Figure 3 (b), it typically employs an auto-regressive loss on the output text tokens. For the attention map in the Transformers [46], image tokens can attend to each other, and the text token depends on and all image tokens and the previous text tokens.



(a) Left: An example of image-to-text generation task; Right: model architecture.



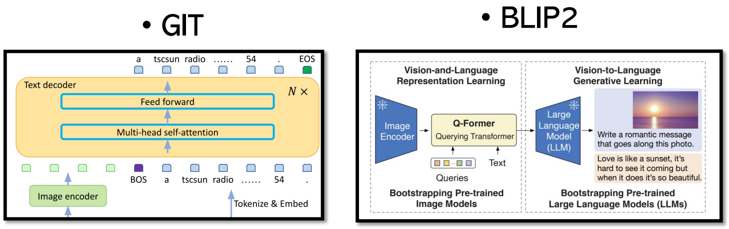
(b) Training objective and attention mask. For each row, the yellow elements indicate that the prediction token attends the tokens on the left.

Figure 3: Illustration of image-to-text generation task, architecture, and training objective.

2.2 Case Studies

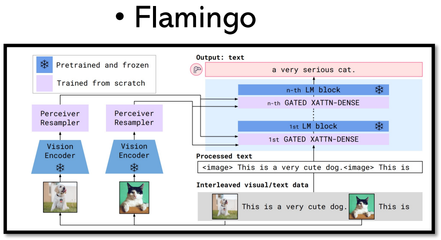
We use some known LMMs as examples to illustrate how the network architecture framework can be instantiated in different models, while maintaining the same auto-regressive training objective.

Case Study I: LMM trained with image-text pairwise instances. Most LMMs are trained on a large number of image-text pairs, where each training sample is a pair. GIT and BLIP2 are two large models that achieve state-of-the-art (SoTA) performance on many datasets. The comparisons are shown in Figure 4(a). GIT [48] initializes image encoder with constrastive pre-trained Microsoft Florence model, and train a language model from scratch. On the other hand, BLIP2 freezes the weights of pre-trained image and language model, and a train lightweight Q-former. BLIP2 [20] shows higher sample-efficiency with the bootstrapping training method.


• GIT
• BLIP2
a
tscsun
radio
......
54
.
EOS
Text decoder
Feed forward
Multi-head self-attention
N ×
BOS
a
tscsun
radio
......
54
.
Image encoder
Tokenize & Embed
Vision-and-Language Representation Learning
Vision-to-Language Generative Learning
Image Encoder
Q-Former
Querying Transformer
Queries
Text
Large Language Model (LLM)
Write a romantic message that goes along this photo.
Love is like a sunset, it's hard to see it coming but when it does it's so beautiful.
Bootstrapping Pre-trained Image Models
Bootstrapping Pre-trained Large Language Models (LLMs)

	GIT	BLIP2
Language Model	From Scratch	Pre-trained: FLAN-T5/OPT
Connection Module		Q-Former: Lightweight Querying Transformer
Vision Encoder	Contrastive pre-trained: Florence/CLIP	Contrastive pre-trained: EVA/CLIP

(a) Example 1: LMM with Image-Text Pairs.



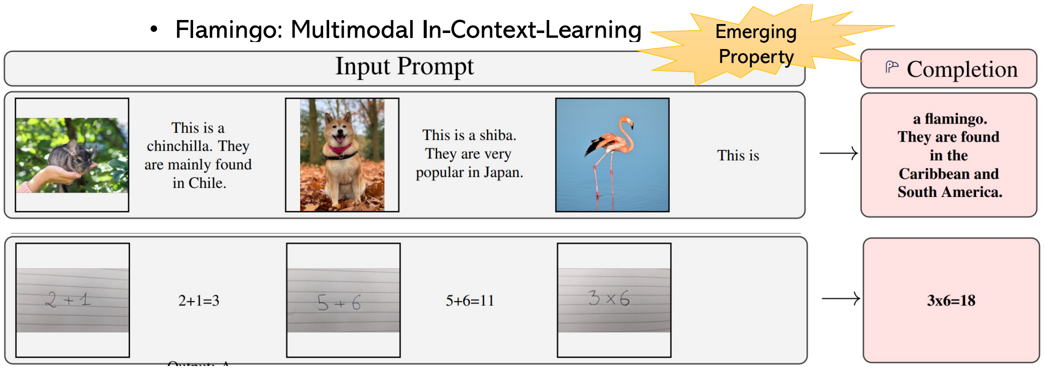
	Flamingo
Language Model	Pre-trained: 70B Chinchilla
Connection Module	Perceiver Resampler Gated Cross-attention + Dense
Vision Encoder	Pre-trained: Nonrmalizer-Free ResNet (NFNet)

(b) Example 2: LMM with Interleaved Image-Text Data.

Figure 4: Examples of image-to-text generation models. Image credits are from [48, 20, 1].

Case Study II: LMM trained with interleaved image-text sequence instances. We use Flamingo [1] as example, shown in Figure 4(b). It connect the frozen pre-trained image and language models – by adding novel architectural components in between. Specifically, Perceiver Sampler module helps reduce compute complexity, and Gated Transformer module helps stabilize training in the initial stage. Flamingo is trained on a mixture of complementary large-scale multimodal data coming only from the web, without using any data annotated for machine learning purposes. After this training is done, Flamingo can be directly adapted to vision tasks via simple few-shot learning without any additional task-specific tuning.

Multimodal In-Context-Learning. Beside the SoTA performance on dozens of academic benchmarks, proabably the most appealing aspect of Flamingo is that it exhibits an emerged property: Multimodal In-Context-Learning. Specifically, given a couple of image-text pairs as examples, Flamingo can zero-shot task transfer to new unseen problems, such as solving visual math problems. This means Flamingo can tackle a number of difficult problems with just a handful of task-specific examples, without any additional training required. For example in Figure 5, two new tasks are presented to Flamingo. The top row provides two image-text pairs as the context in the prompt, where the text describes the name of the animal in the image, followed by the geographical information of the animal. Flamingo is able to understand the patterns in the task instruction illustrated by the examples, and output the corresponding information for a new image. In the bottom row, the text first shows the optical character recognition (OCR) result of the image, followed by the arithmetic result. Flamingo learns the task instruction illustrated in the multimodal context, outputs the correct answer for a new math problem in the image. Therefore, Flamingo is generally considered as the GPT-3 moment [3] in the multimodal domain.

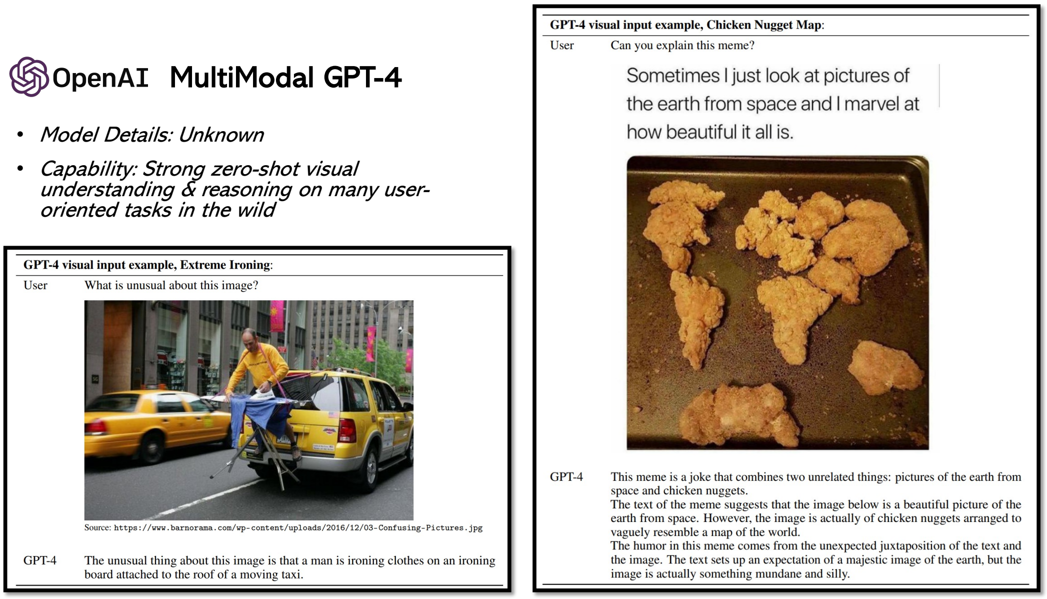


Flamingo: Multimodal In-Context-Learning
Emerging Property
Input Prompt
Completion
This is a chinchilla. They are mainly found in Chile.
This is a shiba. They are very popular in Japan.
This is
a flamingo. They are found in the Caribbean and South America.
2+1
2+1=3
5+6
5+6=11
3x6
3x6=18

Figure 5: The emerging property of pre-training on web-scale interleaved image-text data: multimodal in-context-learning. Visual examples are from [1].

2.3 OpenAI Multimulti GPT4 and Research Gaps

In March 2023, OpenAI released GPT-4 [33], with impressive capability in visual understanding and reasoning. Though the model details are unknown, there is no doubt that GPT4 enables many new scenarios, based on the examples highlighted the technique report. For instance, two popular visual examples are illustrated in Figure 6. The first one identifies the uncommon visual region and exhibits strong complex reasoning performance. The second one recognizes text in the image and captures the mere across image-text. For a while, the research community had no clue how this new ability is achieved (probably because they are not tightened to any established academic tasks/datasets), but all are determined that these are exciting results. It naturally raise a question: How can we build Multimodal GPT-4 like models?



OpenAI MultiModal GPT-4

- *Model Details: Unknown*
- *Capability: Strong zero-shot visual understanding & reasoning on many user-oriented tasks in the wild*

GPT-4 visual input example, Extreme Ironing:

User What is unusual about this image?

Source: https://www.barnorama.com/wp-content/uploads/2016/12/03-Confusing-Pictures.jpg

GPT-4 The unusual thing about this image is that a man is ironing clothes on an ironing board attached to the roof of a moving taxi.

GPT-4 visual input example, Chicken Nugget Map:

User Can you explain this meme?

Sometimes I just look at pictures of the earth from space and I marvel at how beautiful it all is.

GPT-4 This meme is a joke that combines two unrelated things: pictures of the earth from space and chicken nuggets.
The text of the meme suggests that the image below is a beautiful picture of the earth from space. However, the image is actually of chicken nuggets arranged to vaguely resemble a map of the world.
The humor in this meme comes from the unexpected juxtaposition of the text and the image. The text sets up an expectation of a majestic image of the earth, but the image is actually something mundane and silly.

Figure 6: OpenAI MultiModal GPT-4. Visual examples are from [33].

To answer it, we start to review the big models from OpenAI, by highlighting the most appealing properties for each model in Figure 7. There are several key observations: (i) GPT-2 [38] is the auto-regressive counterpart in the BERT era [8] for the paradigm of pre-training then fine-tuning. Compared with GPT-2, GPT-3 [3] is a 175B model trained on web-scale text corpus, which exhibits two emerging properties with a frozen model: in-context-learning [3] and chain-of-thoughts (CoT) reasoning [53].. This means, without any additional training required, the model can tackle a wide range of new problems with just a few task-specific examples and by properly prompting it step-by-step, respectively. It further leads to the paradigm from fine-tuning model weights to prompting

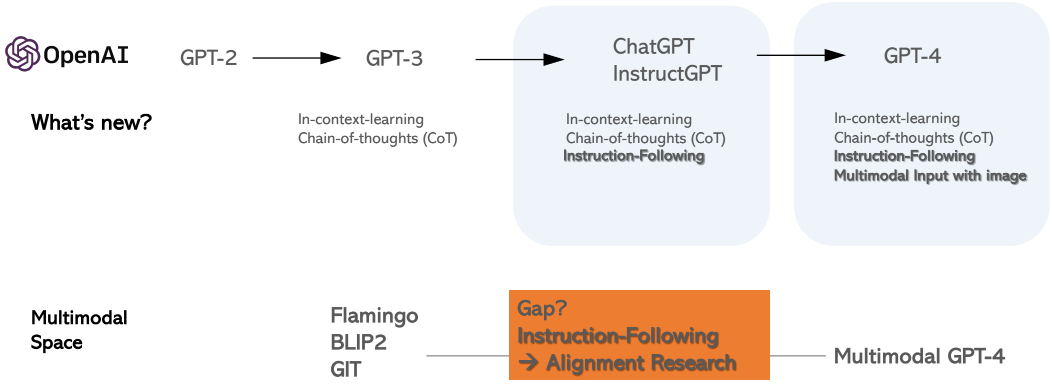


Figure 7: Recap on Language Modeling: OpenAI LLM development history. The unique properties for each generation model is highlighted, from which the research gap is revealed for LMM.

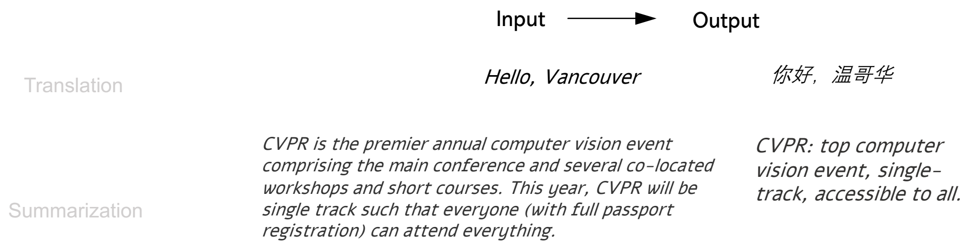
frozen models, where the latter shows higher generality and lower adaptation cost in task transfer. (ii) ChatGPT and InstructGPT [34] shows the importance of instruction-following and alignment with human intents for LLMs, by fine-tuning the base language model GPT-3/GPT-3.5 on high quality instruction-following data, and improving them with a reward model via reinforcement learning with human feedback. (iii) GPT-4 not only improves the language ability of previous models, but also allows visual signals as additional input for understanding and reasoning. We see that the newer generation model maintains/improves the existing properties of the previous ones, and enable new properties.

In another words, from GPT-3 to GPT-4, we see two new properties: instruction-following and multimodal input. This reveals the gap between existing LMMs such as Flamingo and multimodal GPT-4: how to perform instruction-following and alignment research in the multimodal space. and thus the focus of this tutorial & note.

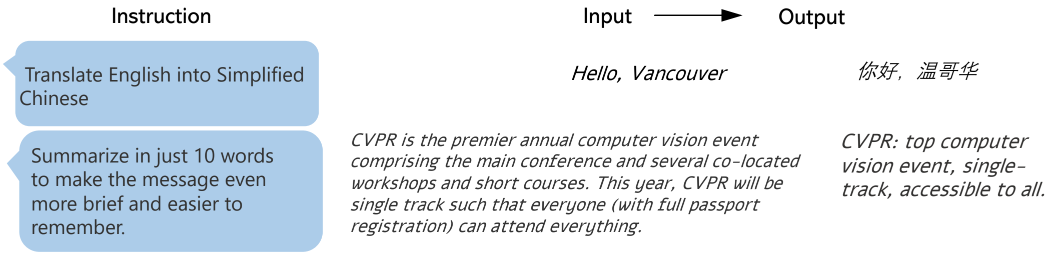
3 Pre-requisite: Instruction Tuning in Large Language Models

Note that instruction-following is a notion originated in natural language processing (NLP). To study the intuition and gain a full picture of the history, we revisit instruction tuning with LLMs.

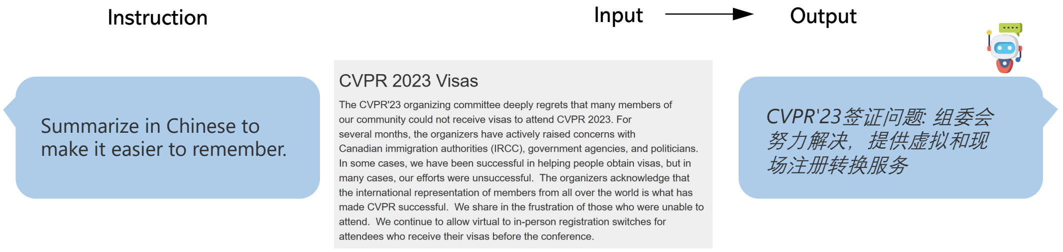
3.1 Instruction Tuning


Input
Output
Translation
Hello, Vancouver
你好，温哥华
Summarization
CVPR is the premier annual computer vision event comprising the main conference and several co-located workshops and short courses. This year, CVPR will be single track such that everyone (with full passport registration) can attend everything.
CVPR: top computer vision event, single-track, accessible to all.

(a) Training: Implicit task instructions in traditional language data.


Instruction
Input
Output
Translate English into Simplified Chinese
Hello, Vancouver
你好，温哥华
Summarize in just 10 words to make the message even more brief and easier to remember.
CVPR is the premier annual computer vision event comprising the main conference and several co-located workshops and short courses. This year, CVPR will be single track such that everyone (with full passport registration) can attend everything.
CVPR: top computer vision event, single-track, accessible to all.

(b) Training: Explicit task instructions in instruct language data.


Instruction
Input
Output
Summarize in Chinese to make it easier to remember.
CVPR'23签证问题: 组委会努力解决，提供虚拟和现场注册转换服务

CVPR 2023 Visas

The CVPR'23 organizing committee deeply regrets that many members of our community could not receive visas to attend CVPR 2023. For several months, the organizers have actively raised concerns with Canadian immigration authorities (IRCC), government agencies, and politicians. In some cases, we have been successful in helping people obtain visas, but in many cases, our efforts were unsuccessful. The organizers acknowledge that the international representation of members from all over the world is what has made CVPR successful. We share in the frustration of those who were unable to attend. We continue to allow virtual to in-person registration switches for attendees who receive their visas before the conference.

(c) Inference: Explicit task instructions in instruct language data. The English meaning of the output is *"CVPR'23 visa issue: organizing committee works to solve and provide virtual and in-person registration switch services."*

Figure 8: Examples of task instructions in traditional and instruct language data, respectively.

Traditional Language Data. As a typical data instance in NLP, seq2seq representation is quite common for many language tasks: each data instance consists of two parts: sequence as the input and sequence as the output. We provide two examples in Figure 8 (a). Without any task instruction specified, we know they are translation and summarization tasks, respectively.

This seq2seq representation is also how NLP community used to use their data. Task instructions are implicit. Based on each data domain, individual models are trained, or sometimes multi-tasking over multiple data domain without specifying the task instructions. When such models are trained, they are hard to generalize to new tasks in a zero-shot fashion, because the models do not learn the skill to understand the task instruction, and have no ability to distinguish and generalize what task to perform in the testing stage.

Instruct Language Data. Instead, recently researchers start to explicitly add task instructions in the model training, as shown in Figure 8 (b). Interestingly, the task instructions of most NLP tasks can be expressed in natural language as well. It leads a new data format: instruction-input-output triplets. Based on the new format, one single model can be trained, multi-tasking with specified instructions. Since models have observed many task instructions and many instances for each task in training, it is natural and easy for the models to generalize to new tasks by task composition in the inference stage.

For example, in the evaluation stage, a new task that require both summarization and translation is provided in Figure 8 (c). Though the model has never seen this new task in training, it observes individual task basis, and learn to perform on new tasks. Note that we humans are always creating new tasks in our daily life, and presumably these new tasks would never been observed by models. It is thus appealing if a model is able to solve thousands of new tasks in the wild in without training. This is partially why ChatGPT is becoming popular and prevalent quickly.

3.2 Self-Instruct and Open-Source LLMs

How can we collect a diverse set of high-quality instruction-following data? There are two general schemes. One is human-human interaction, where humans (task providers) provide the annotation statement and requirements, based on which another group of humans complete the annotation tasks. such a scheme is typically cost and time consuming. The other scheme is human-machine interaction, where similarly humans provide the annotation statement and requirements, but it is now the machines/models that complete the annotation tasks.

To enable LLMs to follow natural language instructions and complete real-world tasks, researchers have been exploring methods of instruction-tuning of LLMs. This is implemented by either fine-tuning the model on a wide range of tasks using human-annotated prompts and feedback [34], or supervised finetuning using public benchmarks and datasets augmented with manually or automatically generated instructions [52]. Among these methods, Self-Instruct tuning [51] is a simple and effective method of aligning LLMs to human intent, by learning from instruction-following data generated by SoTA teacher LLMs. It turns out that the line of instruction-tuning research has produced effective means to improve the zero and few-shot generalization abilities of LLMs. Self-instruct leverages the in-context-learning ability of LLM. The pipeline is illustrated in Figure 9. Humans create a few examples (*i.e.,* seed examples) as the context, and ask LLM such as GPT-3 or GPT-4 to create more instruct and responses that follows the requirements stated in the prompt. The machine-generated instruction-following data can be further selected to construct with the prompt for in-context-learning in the next data generation iteration. The procedure iterates till a given number of samples are collected. Due to the relatively lower cost and higher response speed of API calls (compared with human annotations), self-instruct is becoming more favorable in the research community.

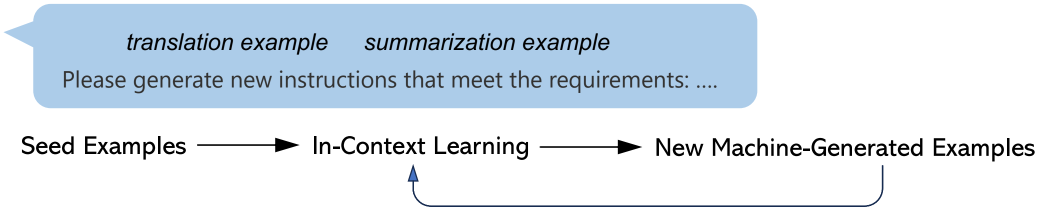

translation example
summarization example
Please generate new instructions that meet the requirements: ....
Seed Examples
In-Context Learning
New Machine-Generated Examples

Figure 9: Self-instruct pipeline.

Open-Source LLMs: LLaMA Family. The open-source community has witnessed a surge of open LLM. The success of ChatGPT [32] and GPT-4 [33] offers tremendous opportunities to improve open-source LLMs using instruction-tuning. Figure 10 compares several open-source instruction tuned LLMs. LLaMA [45] is a series of open-sourced LLMs, which match the performance of proprietary LLMs such as GPT-3. To teach LLaMA to follow instructions, Self-Instruct tuning has been quickly adopted given its superior performance and low cost. For example, to name a few early attempts in this line of research, Stanford Alpaca [43] uses 52K instruction-following samples generated by GPT-3.5, while Vicuna [47] uses around 500K high-quality instruction-following samples (150K conversions) between user and GPT [39]. To advance the SoTA of instruction-tuning for LLMs, GPT-4 is utilized as the teacher to generate the responses for the Alpaca instructions [36]. Many papers have been proposed to improve the instruction-following data to improve the model alignment quality in chat. For a comprehensive review, we suggest the readers to refer the recent paper [50], where a LLM Tulu is trained on a mix of several high-quality instruct data, and comprehensive comparisons are conducted across multiple benchmarks.

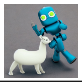
	LLaMA	Alpaca	Vicuna	GPT4-Alpaca 	···	Tulu
Data Source		GPT-3.5	ShareGPT (Human & GPT)	GPT-4 (text-only)	···	Mixed Data
Instruction-following Data (#Turns)	None	52K	500K (~150K conversions)	52K	···	

Figure 10: Model examples of the LLaMA family.

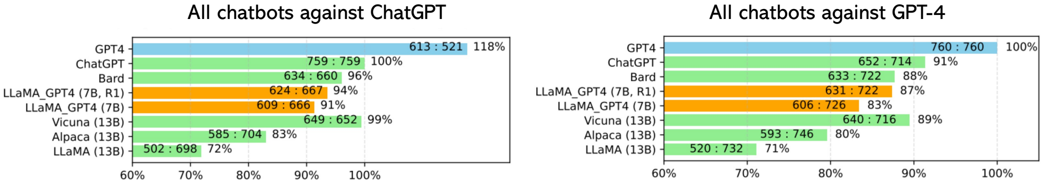


Figure 11: Model performance evaluated on Vicuna-80 questions.

Quick Assessment of LLM Chatbots. To study the quality of LLM Chatbots, We consider *Vicuna-Instructions-80*[2] [47], a dataset with 80 challenging questions that baseline models find challenging. Beside generic instructions, there are 8 categories, including knowledge, math, Fermi, counterfactual, roleplay, generic, coding, writing, common-sense. To quantitatively compare the performance, we ask GPT-4 to rate the response from score 1 to 10 for any two given chatbots, then compute the relative score. The results are shown in Figure 11. Surprisingly, it turns out this evaluation metric is quite consistent across different settings. The open-source LLaMA family seem performing closely to SoTA proprietary Chatbots.

Further Discussions. There are several important topics on LLMs that we have not covered in the tutorial presentation, but are worthwhile future exploring.

- *Data-centric AI*. We emphasize that the developmet of these open-source LLM projects is data-centric [29], rather than model-centric, so that we hope readers could align the perspective when discussing the topic. As the training objective and network architectures are becoming similar and even identical on GPT-like projects, the key differential factor is data. For example, behaviors of the aforementioned LLMs are determined by the instruction tuning data.
- *False Promise?* There is a debate that the open LLMs could catch up with the proprietary LLMs is a false promise [14]. To align the discussions, we argue that there are two distinctive abilities for LLMs: the instruction-following ability to know which task to perform, and massive knowledge storage to complete the task with quality. Imitation models are good at the former, by mimicking ChatGPT's style but not its factuality. They authors in [14] conclude that there exists a substantial capabilities gap between open and closed LMs that, with current methods, can only be bridged using an unwieldy amount of imitation data or by using more capable base LMs. They also advocate that the highest leverage action for improving open-source models is to tackle the difficult challenge of developing better base LMs. However, unfortunately the resources to train such base LMs are only available in a few industry labs, and the formulas to train the base LMs is largely well explored. It seems more promising for most academic research labs to explore the opportunities in alignment research with affordable resources, or explore the techniques to reduce the compute the barriers.
- *Base LLMs*. Developing more capable or commercial usable LLMs is of great value. Besides LLaMA, the open-source community has developed several capable base LLMs such as OpenLLaMA [11], MPT [44] and Falcon [35], or released the training recipe [5].

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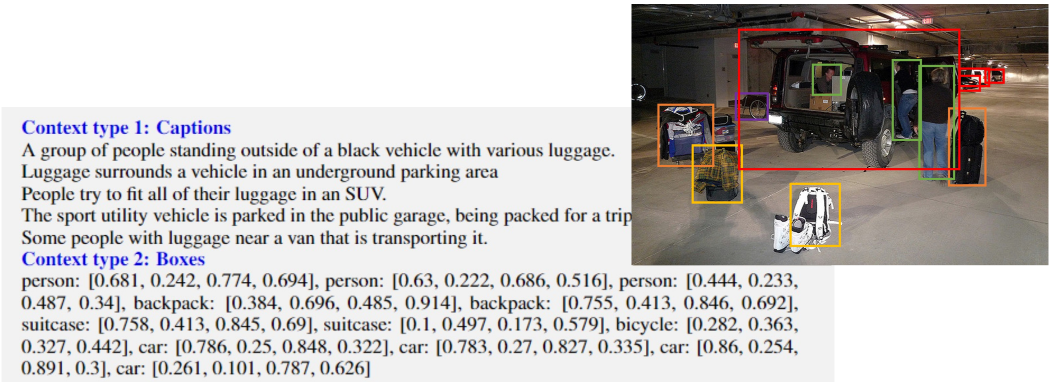
[2] https://github.com/lm-sys/FastChat/blob/main/fastchat/eval/table/question.jsonl

4 Instructed Tuned Large Multimodal Models

In this tutorial, we illustrate how to build the minimum prototype of multimodal GPT4 with open-source resources. Specially, we use LLaVA [24] as the running example, a similar idea is also proposed in its co-current work miniGPT-4 [66].

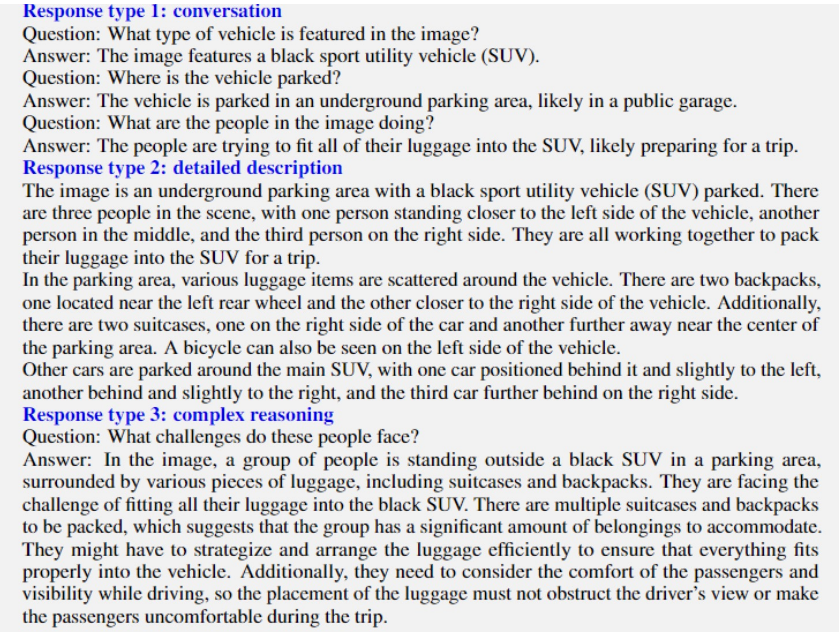
4.1 Open-Source Prototypes: LLaVA / MiniGPT4

The research in the multimodal space has often been inspired by the latest advances in NLP in recent years. One successful recipe is to keep asking what would happen if the most intriguing and successful NLP ideas are borrowed for the vision-and-language community. We are leveraging the self-instruct idea from the language domain. The unique challenge with self-instruct is that there is no strong multimodal teacher available yet. How can we use language model such as language-only GPT-4 to create multimodal instruction following data.



Context type 1: Captions
A group of people standing outside of a black vehicle with various luggage.
Luggage surrounds a vehicle in an underground parking area
People try to fit all of their luggage in an SUV.
The sport utility vehicle is parked in the public garage, being packed for a trip
Some people with luggage near a van that is transporting it.
Context type 2: Boxes
person: [0.681, 0.242, 0.774, 0.694], person: [0.63, 0.222, 0.686, 0.516], person: [0.444, 0.233, 0.487, 0.34], backpack: [0.384, 0.696, 0.485, 0.914], backpack: [0.755, 0.413, 0.846, 0.692], suitcase: [0.758, 0.413, 0.845, 0.69], suitcase: [0.1, 0.497, 0.173, 0.579], bicycle: [0.282, 0.363, 0.327, 0.442], car: [0.786, 0.25, 0.848, 0.322], car: [0.783, 0.27, 0.827, 0.335], car: [0.86, 0.254, 0.891, 0.3], car: [0.261, 0.101, 0.787, 0.626]

(a) The sequence representation of the image data.



Response type 1: conversation
Question: What type of vehicle is featured in the image?
Answer: The image features a black sport utility vehicle (SUV).
Question: Where is the vehicle parked?
Answer: The vehicle is parked in an underground parking area, likely in a public garage.
Question: What are the people in the image doing?
Answer: The people are trying to fit all of their luggage into the SUV, likely preparing for a trip.
Response type 2: detailed description
The image is an underground parking area with a black sport utility vehicle (SUV) parked. There are three people in the scene, with one person standing closer to the left side of the vehicle, another person in the middle, and the third person on the right side. They are all working together to pack their luggage into the SUV for a trip.
In the parking area, various luggage items are scattered around the vehicle. There are two backpacks, one located near the left rear wheel and the other closer to the right side of the vehicle. Additionally, there are two suitcases, one on the right side of the car and another further away near the center of the parking area. A bicycle can also be seen on the left side of the vehicle.
Other cars are parked around the main SUV, with one car positioned behind it and slightly to the left, another behind and slightly to the right, and the third car further behind on the right side.
Response type 3: complex reasoning
Question: What challenges do these people face?
Answer: In the image, a group of people is standing outside a black SUV in a parking area, surrounded by various pieces of luggage, including suitcases and backpacks. They are facing the challenge of fitting all their luggage into the black SUV. There are multiple suitcases and backpacks to be packed, which suggests that the group has a significant amount of belongings to accommodate. They might have to strategize and arrange the luggage efficiently to ensure that everything fits properly into the vehicle. Additionally, they need to consider the comfort of the passengers and visibility while driving, so the placement of the luggage must not obstruct the driver's view or make the passengers uncomfortable during the trip.

(b) The three types of instruction-following data for the given image.

Figure 12: Examples of multimodal instructional-following data. Image credits from [24].

4.1.1 Data Creation

Instead of directly feed images into OpenAI GPT, we use their symbolic sequence representations shown in Figure 12 (a). In LLaVA, the caption and boxes are considered, due to the following

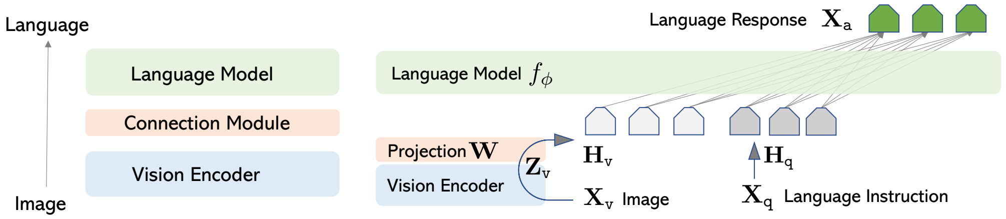


Figure 13: Network architecture: Left: General LMM; Right: LLaVA. Image credits from [24].

reasons: (1) it is empirically found that GPT-4 can understand them well, in contrast that ChatGPT has a difficult time in understanding the box data. (2) they are important to represent the image as informative as possible.

As exemplified in Figure 12 (b), three types of instruction-following data are considered: multi-turn conversations so that users can chat with bot, detailed description so that long response can be generated from the bot; Lastly, complex reasoning, this is more about the implication of the image, rather than the image content. For example, "what challenge do these people face" in this image? The image is about a SUV in the parking area, while the challenge is how the luggage can be packed into the SUV due to the tight space in the car. In total, 158K samples are collected.

To summarize, the trick is that whatever tasks one wants to the model to perform in the serving stage, it is important to create the corresponding instruction-following for the training.

4.1.2 Network Architecture and Training

As illustrated in Figure 13, the LLaVA network architecture is an instantiation of the general image-to-text generative model framework introduced in Section 2 and Figure 3. Specifically, LLaVa connects pre-trained CLIP ViT-L/14 visual encoder [37] and large language model Vicuna [47], using a simple projection matrix. A two-stage instruction-tuning procedure is considered:

- *Stage 1: Pre-training for Feature Alignment.* Only the projection matrix is updated, based on a subset of CC3M [40]. The only task is image captioning.
- *Stage 2: Fine-tuning End-to-End.* Both the projection matrix and LLM are updated for two different use scenarios.

4.1.3 Performance

Performance on Visual Chat: Towards building multimodal GPT-4 level chatbot. . LLaVA is fine-tuned on the generated multimodal instruction-following data, which contains a diverse set of task instruction and response for daily user-oriented applications. It is empirically found that fine-tuning the linear projection layer only is sufficient for the chat demo/scenarios, though it requires longer training time.

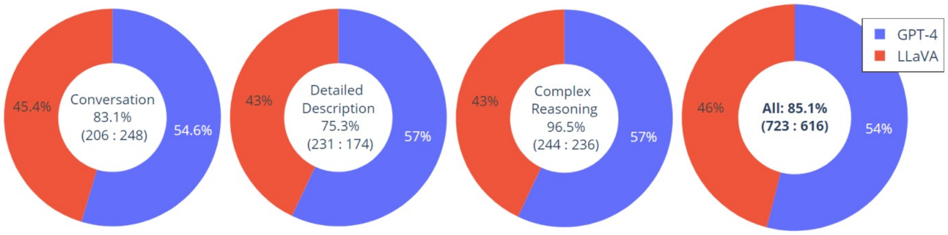
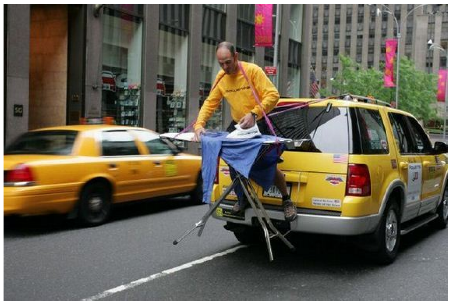


Figure 14: Visual chat performance: LLaVA vs GPT-4. Image credits from [24].

An evaluation dataset with 30 unseen images is constructed: each image is associated with three types of instructions: conversation, detailed description and complex reasoning. This leads to 90 new language-image instructions, on which we test LLaVA and GPT-4, and use GPT-4 to rate their responses from score 1 to 10. The summed score and relative score per type is reported in Figure 14. Overall, LLaVA achieves 85.1% relative score compared with GPT-4, indicating the effectiveness of the proposed self-instruct method in multimodal settings.

Visual input example, Extreme Ironing:



Source: `https://www.barnorama.com/wp-content/uploads/2016/12/03-Confusing-Pictures.jpg`

User	What is unusual about this image?
LLaVA	The unusual aspect of this image is a man ironing clothes on the back of a minivan or van. This is not a typical place to perform this activity, as one would usually iron clothes in a more stationary and safe location, such as a home, using a regular ironing board. The scene depicted in the image is peculiar as it involves a makeshift ironing setup on a vehicle, which can be both unsafe and unconventional. Additionally, it is not clear how the man is able to maintain balance and stability while ironing clothes in such an unstable environment.
	[*Start a new conversation, and clear the history*]
User	What's happening in the scene?
LLaVA	The image depicts a man standing on top of a yellow SUV in a busy city street. He is holding a portable ladder, seemingly ironing clothes while standing on the vehicle. Around the scene, there are other cars, a traffic light, and a fire hydrant. Additionally, there are two other people in the vicinity, one close to the man on the car and another further away. The man on the ladder appears to be attracting attention due to his unconventional choice of ironing his clothes on top of a moving car. The city street around him is bustling with activity, adding to the unique nature of the scene.
User	What is unusual about this image?
GPT-4 [33]	The unusual thing about this image is that a man is ironing clothes on an ironing board attached to the roof of a moving taxi.
User	What is unusual about this image?
MiniGPT-4	The image shows a man standing on the back of a yellow taxi cab, holding a piece of clothing in his hand. The taxi is parked on a busy street with other cars passing by. The man is wearing a yellow shirt and has a look of determination on his face. The image is unusual because it shows a person standing on the back of a taxi, which is not a common sight in most cities.
User	What is unusual about this image?
BLIP-2	a man is sitting on the back of a yellow cab
User	What is unusual about this image?
OpenFlamingo	The man is drying his clothes on the hood of his car.

Table 1: Example prompt from GPT-4 paper [33] to compare visual reasoning and chat capabilities. Compared to BLIP-2 [20] and OpenFlamingo [2], LLaVA accurately follows the user's instructions, instead of simply describing the scene. LLaVA offers a more comprehensive response than GPT-4. Even when merely asked to describe the image, LLaVA identifies atypical aspects of the image. Table credits from [24].

More examples are shown in Table 1 and Table 2, respectively.

Performance on Science QA: New SoTA with the synergy of LLaVA with GPT-4. LLaVA is fine-tuned on a multimodal reasoning dataset in the science domain [26]. In Figure 15, LLaVA alone achieves 90.92%. We use the language-only GPT-4 as the judge, to predict the final answer based on its own previous answers and the LLaVA answers. This "GPT-4 as judge" scheme yields a new SoTA 92.53%.

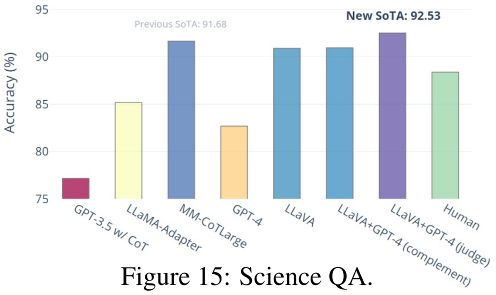


Figure 15: Science QA.

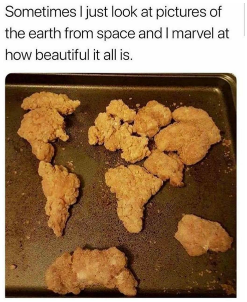
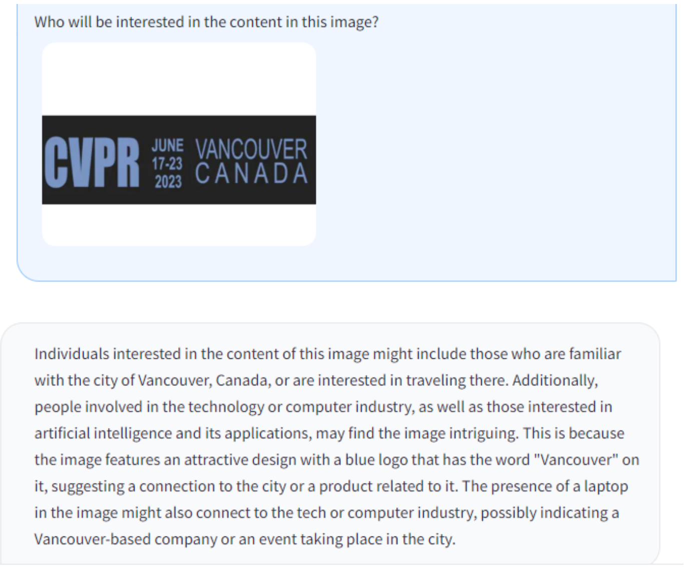
Visual input example, Chicken Nugget Map:	
	 Sometimes I just look at pictures of the earth from space and I marvel at how beautiful it all is.
User	Can you explain this meme in detail?
LLaVA	The meme in the image is a creative and humorous take on food, with a focus on chicken nuggets, as the center of the universe. The meme begins with the phrase "Sometimes I just look at pictures of the Earth from space and I marvel at how beautiful it all is..." The main image features a tray of cooked chicken nuggets, with the chicken pieces positioned to resemble the continents and islands on a world map. The meme playfully suggests that the chicken nuggets represent the Earth, and the various locations depicted in the photo are actually chicken nugget versions of different places. The punchline of the meme appears in smaller text at the bottom, reading "I mean, it's not the real Earth, but how beautiful it is all is." This lighthearted and entertaining meme combines food and humor, using the image of chicken nuggets to create a funny and imaginative representation of the world.
User	Can you explain this meme?
GPT-4 [33]	This meme is a joke that combines two unrelated things: pictures of the earth from space and chicken nuggets. The text of the meme suggests that the image below is a beautiful picture of the earth from space. However, the image is actually of chicken nuggets arranged to vaguely resemble a map of the world. The humor in this meme comes from the unexpected juxtaposition of the text and the image. The text sets up an expectation of a majestic image of the earth, but the image is actually something mundane and silly.
User	Can you explain this meme in detail?
MiniGPT-4	This meme is a picture of a pan full of fried chicken. The chicken is cooked and appears to be ready to be served. The caption reads, "Sometimes it's just like looking at pictures from space and marveling at how beautiful it all is." This meme is likely meant to be humorous and playful, as it compares the beauty of space to the simple pleasure of eating fried chicken. It is likely meant to be a lighthearted and funny way to express appreciation for both the wonders of space and the simple pleasures of food.
User	Can you explain this meme in detail?
BLIP-2	sometimes i just look at pictures of the earth from space and marvel how beautiful it is
User	Can you explain this meme in detail?
OpenFlamingo	It's a picture of a chicken nugget on the International Space Station.

Table 2: Example prompt comparing LLaVA, GPT-4, BLIP-2, and OpenFlamingo's visual reasoning capabilities in understanding the humor. LLaVA and GPT-4 both explain the meme and its humor, while GPT-4 produces a more concise answer. Table credits from [24].

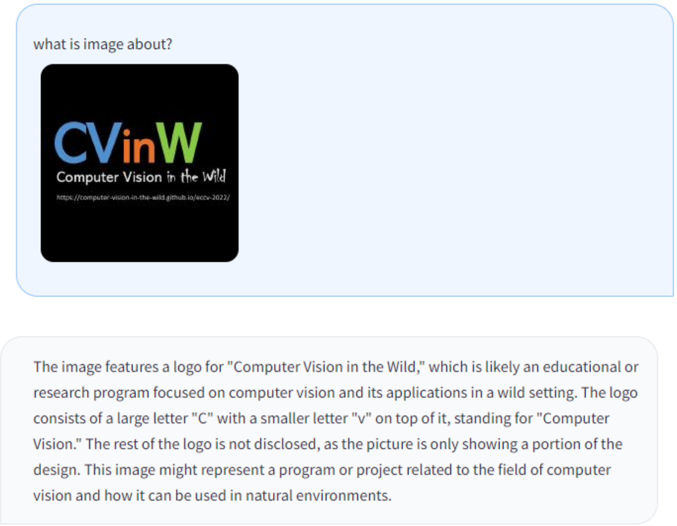
Performance on OCR in the wild: An emerging property. LLaVA has never been explicitly trained on OCR data, *i.e.,* images that contains text from the corresponding caption. Surprisingly, the model show strong zero-shot OCR task transfer ability in the wild. Some examples are shown in Figure 16.



Who will be interested in the content in this image?

Individuals interested in the content of this image might include those who are familiar with the city of Vancouver, Canada, or are interested in traveling there. Additionally, people involved in the technology or computer industry, as well as those interested in artificial intelligence and its applications, may find the image intriguing. This is because the image features an attractive design with a blue logo that has the word "Vancouver" on it, suggesting a connection to the city or a product related to it. The presence of a laptop in the image might also connect to the tech or computer industry, possibly indicating a Vancouver-based company or an event taking place in the city.

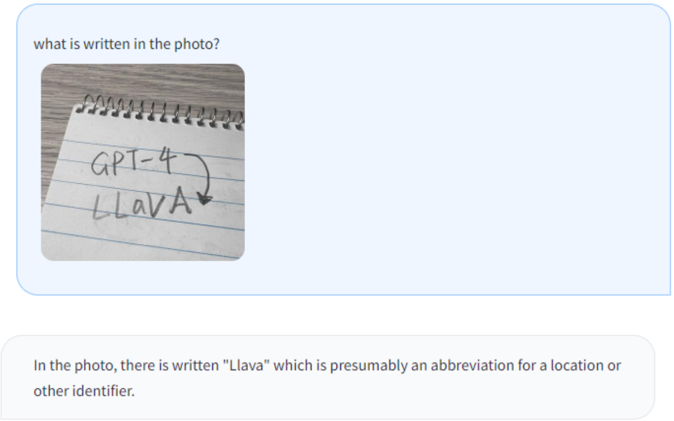
(a) CVPR 2023 logo. `https://cvpr2023.thecvf.com/`


CVinW
Computer Vision in the Wild
https://computer-vision-in-the-wild.github.io/eccv-2022/

what is image about?

The image features a logo for "Computer Vision in the Wild," which is likely an educational or research program focused on computer vision and its applications in a wild setting. The logo consists of a large letter "C" with a smaller letter "v" on top of it, standing for "Computer Vision." The rest of the logo is not disclosed, as the picture is only showing a portion of the design. This image might represent a program or project related to the field of computer vision and how it can be used in natural environments.

(b) CVinW workshop logo. `https://github.com/Computer-Vision-in-the-Wild`



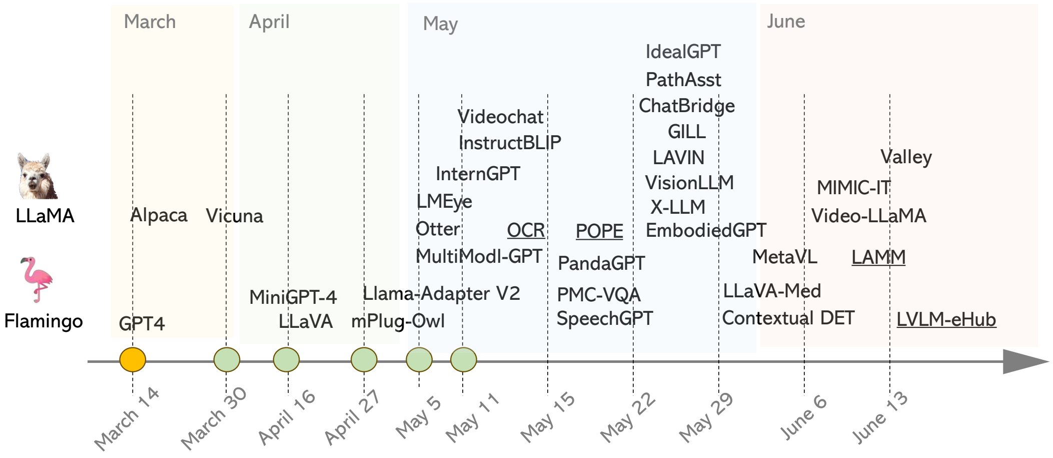
what is written in the photo?

In the photo, there is written "Llava" which is presumably an abbreviation for a location or other identifier.

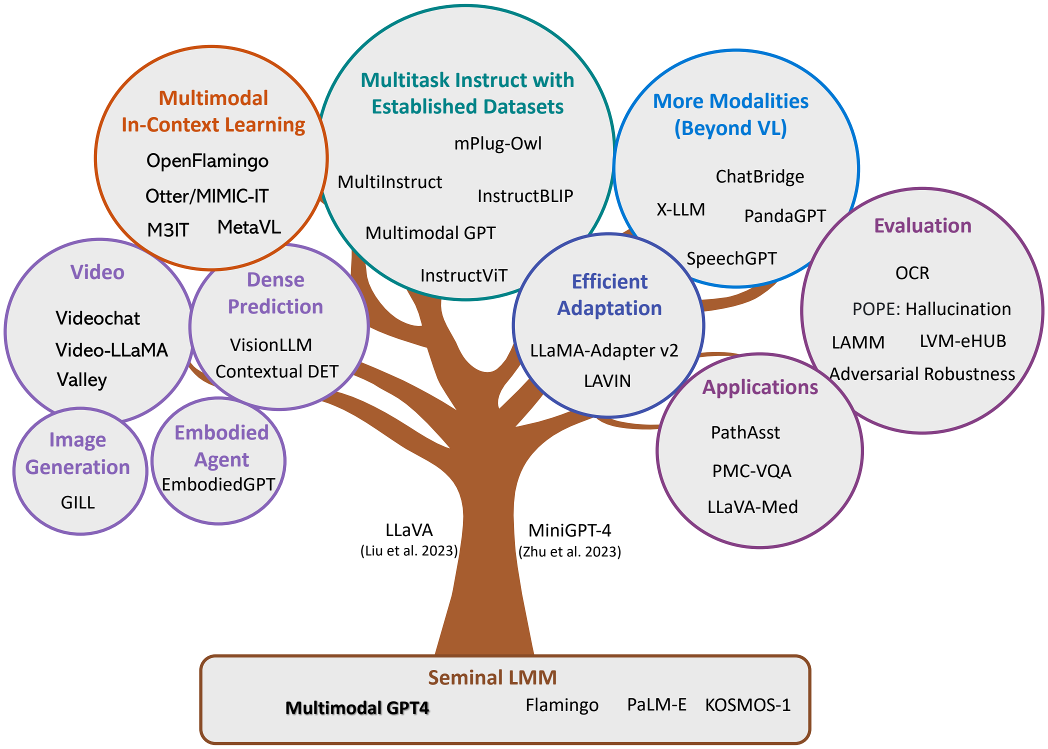
(c) Hand-written "LLaVA". `https://llava-vl.github.io/`

Figure 16: Examples that LLaVA is able to recognize and reasons with text in the images in the wild.

4.2 Emerging Topics



(a) The surge of papers on LMMs in the past three months: March 14 - June 19, 2023. Those with an underline indicate benchmarks, otherwise indicate models.



(b) Summary and categorization of papers on LMMs.

Figure 17: Review and summary for the emerged LMM literature.

The history of recent instructed tuned LMM are illustrated in Figure 17 (a). Due to the popularity of ChatGPT and GPT-4, instructed tuned LMM appears as an emerging line of research in the past three months after GPT-4 was proposed. Alpaca and Vicuna were proposed to make LLaMA more instruction-following in the language domain in March. In two weeks, MiniGPT-4 and LLaVA were proposed to make Vicuna to see and chat about the visual world. In ten days, Llama-Adpter v2 and mPlug-OWL started to compare performance with MiniGPT-4/LLaVA, indicating the beginning of model evolution. The data points in April are relatively sparse. In May, a large number of LMM papers appeared on arXiv, which improve this line of research from many different aspects. The momentum is till going in June.

It is easy to lose track of all the recent papers for the readers, so as well in our literature review. To better organize the literature, we group them based on specific research topics in this tutorial, shown in Figure 17 (b). The early LMMs with billions of parameters include GPT-4 [33], Flamingo [1], PaLM-E [9] and KOSMOS-1 [15]. In constrast to these proprietary LMMs, LLaVA/MiniGPT-4 open the opportunities to build LMMs with open-source resource. We will discuss the several topics as below, in addition to dense prediction [49, 60], video [62, 28, 21], image generation [16] and embodied agent [31].

4.2.1 More Modalities (Beyond VL)

- *ChatBridge: Bridging Modalities with Large Language Model as a Language Catalyst [65]*
- *PandaGPT: One Model To Instruction-Follow Them All [41]*
- *SpeechGPT: Empowering large language models with intrinsic cross-modal conversational abilities [61]*
- *X-LLM: Bootstrapping Advanced Large Language Models by Treating Multi-Modalities as Foreign Languages [4]*

While LMM extends LLM by adding the vision modality into language, it is natural to further extend the framework to include more modalities beyond vision and language. Following this spirit, several attempts have been made. In Figure 18, PandaGPT leverages ImageBind to add more modalities into LMMs. The ImageBind model [12] learns a single, shared representation space for text, image/video, audio, sensors that record depth (3D), thermal (infrared radiation), and inertial measurement units (IMU), which calculate motion and position. ImageBind provides a holistic understanding of the visual world that connects objects in a photo with how they will sound, their 3D shape, how warm or cold they are, and how they move. By training a projection layer for one modality in LMM, the model can zero-shot transfer to infer over other modalities due to the shared multimodal embedding space. Another representative model is SpeechGPT, where language and speech modalities are enabled for both input and output ends. Despite of rich model variations, the idea to connect diverse modalities is similar to LMM that adds images into LLMs.

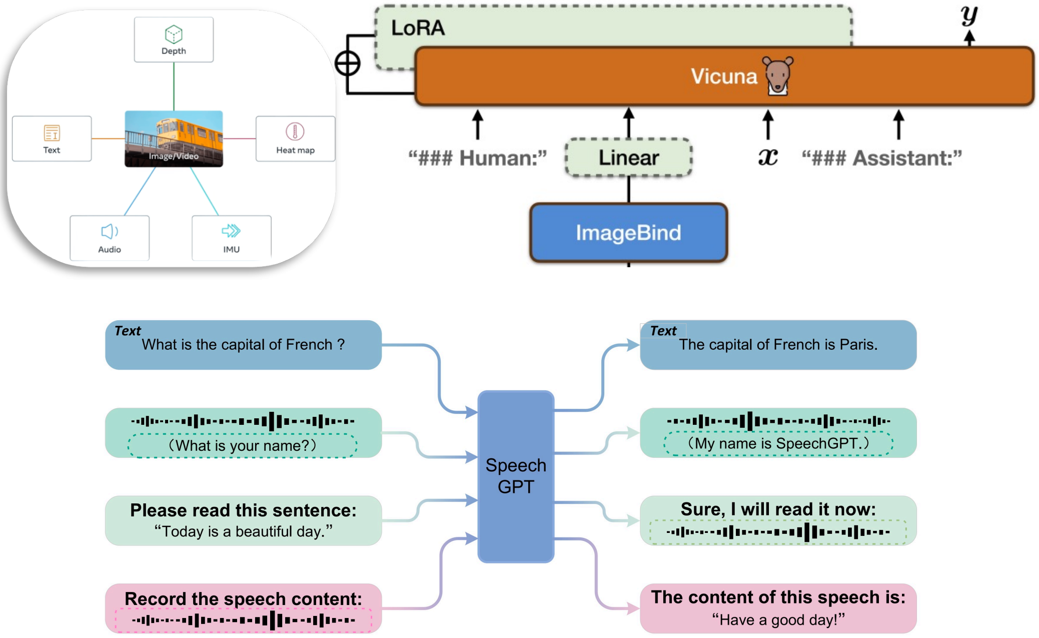

Depth
Text
Image/Video
Heat map
Audio
IMU
LoRA
y
Vicuna
"### Human:"
Linear
x
"### Assistant:"
ImageBind
Text
What is the capital of French ?
(What is your name?)
Please read this sentence:
"Today is a beautiful day."
Record the speech content:
Speech GPT
Text
The capital of French is Paris.
(My name is SpeechGPT.)
Sure, I will read it now:
The content of this speech is:
"Have a good day!"

Figure 18: LLMs with more modalities. Top: PandaGPT that enables other modalities via ImageBind; Bottom: SpeechGPT that allows language and speech in both input and output. Image credits from [41, 61].

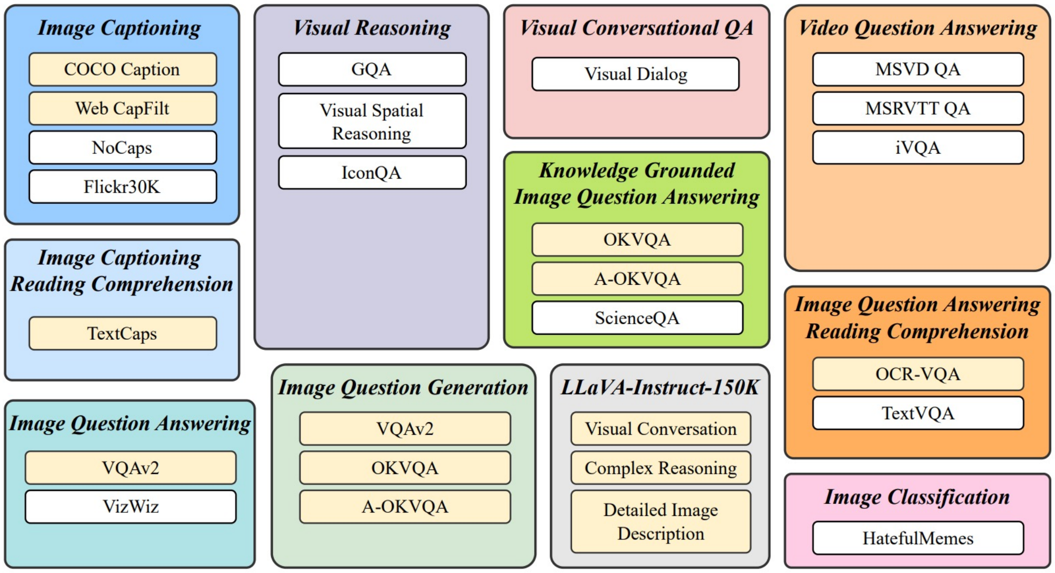


Figure 19: The vision-language tasks covered in InstructBLIP. Image credits from [6].

4.2.2 Multitask Instruct with Established Academic Datasets/Tasks

- *MultiInstruct: Improving Multi-Modal Zero-Shot Learning via Instruction Tuning [57]*
- *mPlug-OWL: Modularization empowers large language models with multimodality [58]*
- *InstructBLIP: Towards general-purpose vision-language models with instruction tuning [6]*
- *Multimodal-GPT: A vision and language model for dialogue with humans [13]*
- *Instruction-ViT: Multi-Modal Prompts for Instruction Learning in ViT [54]*

As discussed earlier in Section 3, instruction tuning in the language domains is implemented in two different ways: fine-tuning the model on a wide range of tasks using human-annotated prompts and feedback [34], or supervised fine-tuning using public benchmarks and datasets augmented with manually or automatically generated instructions [52]. The former is good at user-oriented daily life tasks, and the latter is good at achieving good numbers on established benchmarks. LLaVA/MiniGPT-4 can be categorized as the former class. Several other works either target for the latter class or combine both classes.

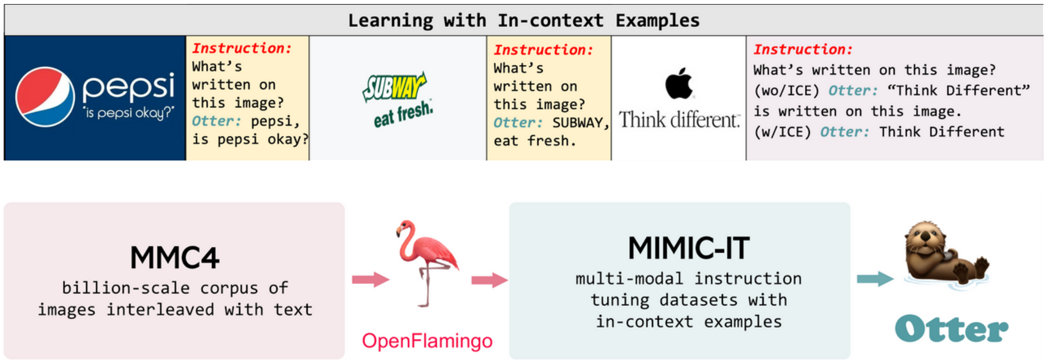
For example, MultiInstruct is an early attempt before open-source LLaMA for instruction tuning with multimodal datasets. InstructBLIP is recent work that combine chat and benchmark instruction-following data. As shown in Figure 19, there are 26 publicly available datasets, covering a wide variety of tasks and capabilities, and transform them into instruction tuning format. Trained on 13 held-in datasets, InstructBLIP attains SoTA zero-shot performance across all 13 held-out datasets, substantially outperforming BLIP-2 and larger Flamingo models.

4.2.3 Multimodal In-Context-Learning

- *OpenFlamingo [2]*
- *Otter: A Multi-Modal Model with In-Context Instruction Tuning [18]*
- *M^3IT: A Large-Scale Dataset towards Multi-Modal Multilingual Instruction Tuning [22]*
- *MetaVL: Transferring In-Context Learning Ability From Language Models to Vision-Language Models [30]*

Similar to the behaviour of LLMs, which can address a language task by processing examples of the task in their text prompt, multimodal in-context-learning refers to an visual and text interface can steer the model towards solving a multimodal task. Given a few example pairs of visual inputs and expected text responses composed in the multimodal prompt, the model can be asked a question with a new image or video, and then generate an answer.

OpenFlamingo [2] is an open source version of DeepMind's Flamingo model, trained on Multimodal C4 dataset [67], which is a billions-scale corpus of image interleaved with text. To explicit enhance the multimodal in-context-learning ability of LMMs, MIMIC-IT [17] dataset is constructed, which is 2.4M multimodal instruction instances with in-context examples. By tuning OpenFlamingo on MIMIC-IT, a new model Otter is obtained with a stronger instruction-following ability. The model life cycle is summarized in Figure 20. Using two image-text pairs as the context, Otter learns the concise answering style demonstrated by the examples, otherwise a tedious response is generated.


Learning with In-context Examples
pepsi
"is pepsi okay?"
SUBWAY
eat fresh.
Think different.
MMC4
billion-scale corpus of images interleaved with text
OpenFlamingo
MIMIC-IT
multi-modal instruction tuning datasets with in-context examples
Otter

Instruction: What's written on this image? Otter: pepsi, is pepsi okay?

Instruction: What's written on this image? Otter: SUBWAY, eat fresh.

Instruction: What's written on this image? (wo/ICE) Otter: "Think Different" is written on this image. (w/ICE) Otter: Think Different

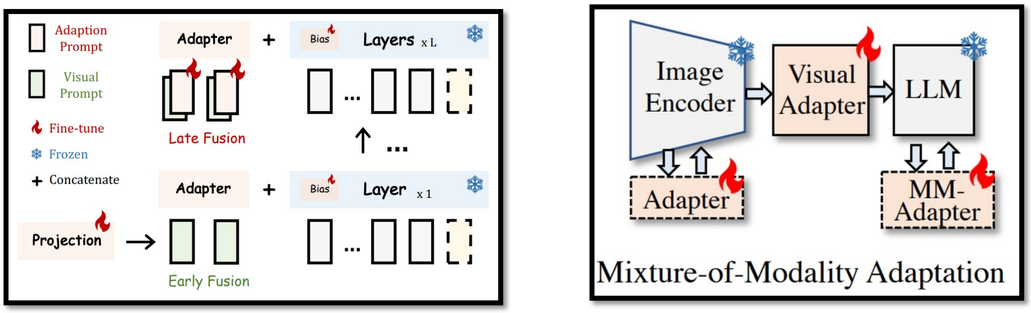
Figure 20: Top: Illustration of multimodal in-context-learning of Otter. Bottom: the training process from OpenFlamingo to Otter. Image credits from [17].

4.2.4 Parameter-Efficient Training

- *LLaMA-Adapter V2: Parameter-Efficient Visual Instruction Model [10]*
- *Cheap and Quick: Efficient Vision-Language Instruction Tuning for Large Language Models [27]*
- *QLoRA: Efficient Finetuning of Quantized LLMs [7]*

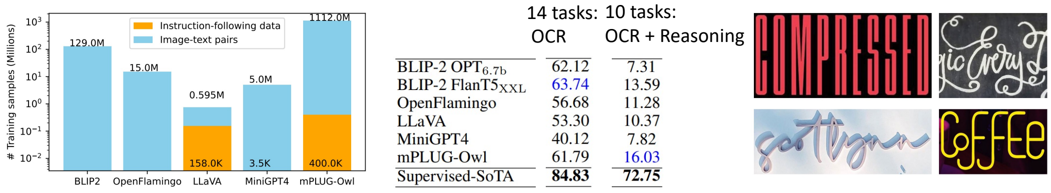
While fine-tuning very large models often leads to high performance, it is prohibitively expensive; For example, regular 16-bit fine-tuning of a LLaMA 65B parameter model [45] requires more than 780 GB of GPU memory [7]. Therefore, it is critical to reduce the memory footprint of LLMs/LMMs, especially when it comes to improve the accessibility of large models to a wider community.

Parameter-efficient training is an effective approach for LMM adaptation. Two representative methods are illustrated in Figure 21. They freeze most of the model parameters, and only allow a small of trainable parameter to update with domain specific data. For example, LLaMA Adapter v2 and LAVIN only has 14M and 3.8M trainable parameters, compared with 7B/13B LLM parameters. Another efficient training method is quantization. The recent QLoRA finetunes 65B LLaMA for 24 hours on a single GPU, reaching 99.3% of the performance level of ChatGPT. Since instruction tuning typically involves a small amount of data, it makes parameter-efficient training or model quantization feasible with limited GPU resources.



LLaMA-Adapter V2: 14M parameters LAVIN: 3.8M parameters

Figure 21: Parameter-efficient methods for LMMs. Image credits from [10, 27].



	14 tasks: OCR	10 tasks: OCR + Reasoning
BLIP-2 OPT$_{6.7b}$	62.12	7.31
BLIP-2 FlanT5$_{XXL}$	63.74	13.59
OpenFlamingo	56.68	11.28
LLaVA	53.30	10.37
MiniGPT4	40.12	7.82
mPLUG-Owl	61.79	16.03
Supervised-SoTA	**84.83**	**72.75**

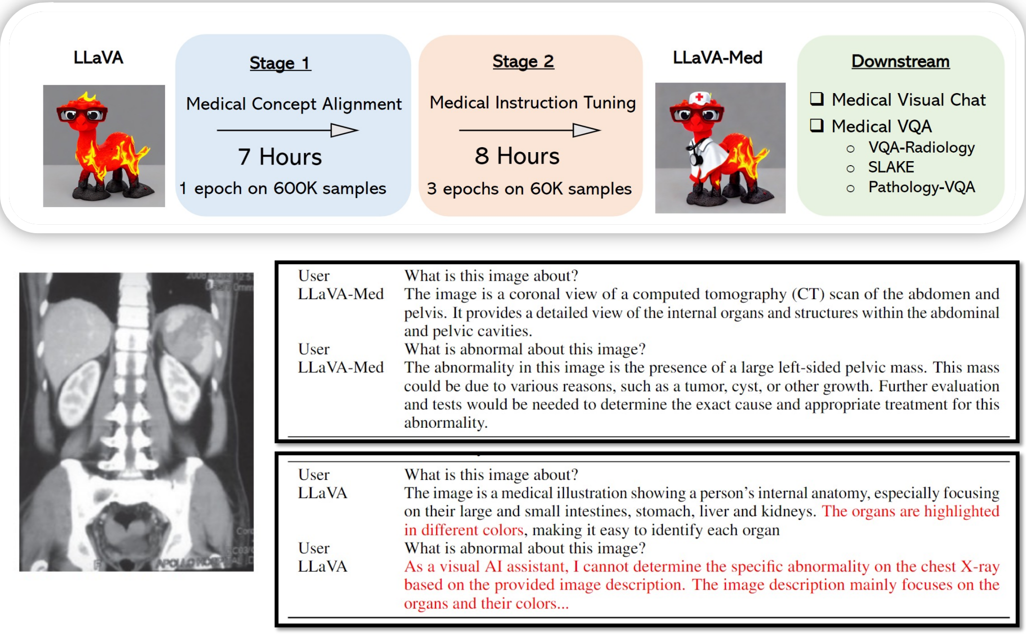
Figure 22: Zero-shot OCR performance of LMMs on 24 datasets. Image credits from [25].

4.2.5 Benchmarks

- *On the Hidden Mystery of OCR in Large Multimodal Models [25]*
- *Evaluating Object Hallucination in Large Vision-Language Models [23]*
- *On Evaluating Adversarial Robustness of Large Vision-Language Models [64]*
- *LAMM: Language-Assisted Multi-Modal Instruction-Tuning Dataset, Framework, and Benchmark [59]*
- *LVLM-eHub: A Comprehensive Evaluation Benchmark for Large Vision-Language Models [56]*

While LMMs have shown excellent visual recognition and reasoning in an open-set manner with free-form text in many scenarios, the evaluation of LMMs is becoming an urgent and challenging problem. Several related benchmarks have been developed to evaluate various aspects of LMMs, ranging from their specific abilities including OCR[25], object hallucination [23] and adversarial robustness [64], to comprehensive evaluation [59, 56].

It is surprising that LMMs shows strong zero-shot OCR performance in the wild, without explicitly training on text recognition data. To shed light on the hidden mystery of OCR in LMMs, a comprehensive empirical study is conducted in [25] to compare open-source LMMs on 24 academic text recognition datasets, shown in Figure 22. Three observations are highlighted: (1) LLaVA consistently outperforms miniGPT-4 on 21 out of 24 datasets, despite LLaVA being trained with an order of magnitude smaller training data. (2) Training with significantly larger training data leads to higher OCR performance, as demonstrated by BLIP2 [20] and mPLUG-Owl. (3) In most cases, supervised SoTA results significantly outperform zero-shot LMM. However, it is worth noting that in the WordArt dataset [55], which primarily features challenging artistic text, BLIP2 surpasses supervised SoTA. This reveals the potential of LMM in recognizing more complex text types.



User	What is this image about?
LLaVA-Med	The image is a coronal view of a computed tomography (CT) scan of the abdomen and pelvis. It provides a detailed view of the internal organs and structures within the abdominal and pelvic cavities.
User	What is abnormal about this image?
LLaVA-Med	The abnormality in this image is the presence of a large left-sided pelvic mass. This mass could be due to various reasons, such as a tumor, cyst, or other growth. Further evaluation and tests would be needed to determine the exact cause and appropriate treatment for this abnormality.

User	What is this image about?
LLaVA	The image is a medical illustration showing a person's internal anatomy, especially focusing on their large and small intestines, stomach, liver and kidneys. The organs are highlighted in different colors, making it easy to identify each organ
User	What is abnormal about this image?
LLaVA	As a visual AI assistant, I cannot determine the specific abnormality on the chest X-ray based on the provided image description. The image description mainly focuses on the organs and their colors...

Figure 23: Application of LMMs to bio-medicine. Top: The domain adaptation from LLaVA to LLaVA-Med. Bottom: The chat behaviors of two chatbots. Image credits from [19].

4.2.6 Applications

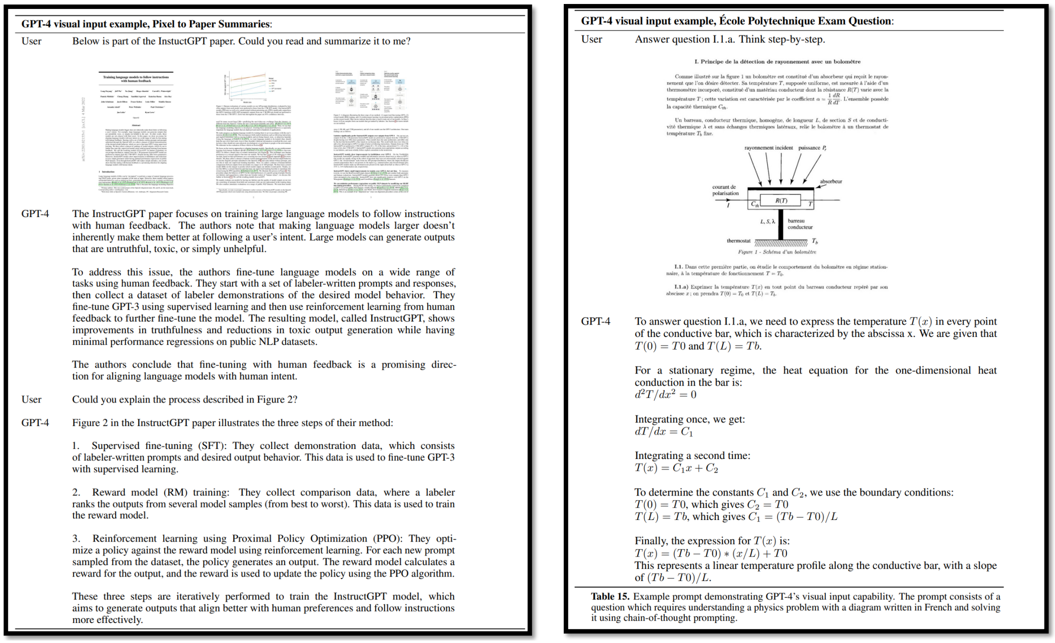
- *PathAsst: Redefining Pathology through Generative Foundation AI Assistant for Pathology [42]*
- *PMC-VQA: Visual Instruction Tuning for Medical Visual Question Answering [63]*
- *LLaVA-Med: Training a Large Language-and-Vision Assistant for Biomedicine in One Day [19]*

The success of ChatGPT/GPT-4 in the general domain has inspired the interests in building assistants in the vertical domains such as medicine, gaming and education. Such domain-specific assistants can have the several advantages over the general domain counterpart: (1) training high-quality domain knowledge makes the assistants more helpful, (2) the model size can be smaller, and thus severing cost is low, (3) the sensitive user prompt data can be maintained internally by serving the model at local, and the privacy issue can be avoided.

LMMs have been recently explored in the biomedical domain [42, 63, 19], where conversational generative AI has demonstrated remarkable promise for empowering biomedical practitioners. LLaVA-Med is a cost-efficient approach for training a vision-language conversational assistant that can answer open-ended research questions of biomedical images. The key idea is to leverage a large-scale, broad-coverage biomedical figure-caption dataset extracted from PubMed Central, use GPT-4 to self-instruct open-ended instruction-following data from the captions, and then fine-tune a large general-domain vision-language model LLaVA using a novel curriculum learning method. Specifically, the model first learns to align biomedical vocabulary using the figure-caption pairs as is, then learns to master open-ended conversational semantics using GPT-4 generated instruction-following data, broadly mimicking how a layperson gradually acquires biomedical knowledge. In Figure 23, we provide examples on the biomed visual conversations of different chatbots. LLaVA-Med precisely answers the questions with biomedical knowledge, while LLaVA behaves like a layperson, who hallucinate based on commonsense.

5 How Close We Are with OpenAI Multimodal GPT-4?

With all these new works, are we close or even surpassing OpenAI Multimodal GPT-4? It is encouraging to see that the open-source community has quickly developed a variety of models and prototypes for various new capabilities. For example, LLaVA/Mini-GPT4 paves the way towards building multimodal chatbots, with some examples that reproduce the results in OpenAI GPT-4 technique report; GILL [16] extends LMMs for end-to-end image generation, to our best knowledge, this is a capability that the current GPT-4 does not exhibit. From the perspective of enabling new multimodal capabilities with the minimum prototypes, the open-source community seems close to OpenAI Multimodal GPT-4, by exploring the baby steps towards building the general-purpose multimodal assistant.



GPT-4 visual input example, Pixel to Paper Summaries:

User Below is part of the InstuctGPT paper. Could you read and summarize it to me?

GPT-4 The InstructGPT paper focuses on training large language models to follow instructions with human feedback. The authors note that making language models larger doesn't inherently make them better at following a user's intent. Large models can generate outputs that are untruthful, toxic, or simply unhelpful.

To address this issue, the authors fine-tune language models on a wide range of tasks using human feedback. They start with a set of labeler-written prompts and responses, then collect a dataset of labeler demonstrations of the desired model behavior. They fine-tune GPT-3 using supervised learning and then use reinforcement learning from human feedback to further fine-tune the model. The resulting model, called InstructGPT, shows improvements in truthfulness and reductions in toxic output generation while having minimal performance regressions on public NLP datasets.

The authors conclude that fine-tuning with human feedback is a promising direction for aligning language models with human intent.

User Could you explain the process described in Figure 2?

GPT-4 Figure 2 in the InstructGPT paper illustrates the three steps of their method:

1. Supervised fine-tuning (SFT): They collect demonstration data, which consists of labeler-written prompts and desired output behavior. This data is used to fine-tune GPT-3 with supervised learning.

2. Reward model (RM) training: They collect comparison data, where a labeler ranks the outputs from several model samples (from best to worst). This data is used to train the reward model.

3. Reinforcement learning using Proximal Policy Optimization (PPO): They optimize a policy against the reward model using reinforcement learning. For each new prompt sampled from the dataset, the policy generates an output. The reward model calculates a reward for the output, and the reward is used to update the policy using the PPO algorithm.

These three steps are iteratively performed to train the InstructGPT model, which aims to generate outputs that align better with human preferences and follow instructions more effectively.

GPT-4 visual input example, École Polytechnique Exam Question:

User Answer question I.1.a. Think step-by-step.

I. Principe de la détection de rayonnement avec un bolomètre

Comme illustré sur la figure 1 un bolomètre est constitué d'un absorbeur qui reçoit le rayonnement que l'on désire détecter. Sa température T, supposée uniforme, est mesurée à l'aide d'un thermomètre incorporé, constitué d'un matériau conducteur dont la résistance $R(T)$ varie avec la température T ; cette variation est caractérisée par le coefficient $\alpha = \frac{1}{R}\frac{dR}{dT}$. L'ensemble possède la capacité thermique C_{th}.

Un barreau, conducteur thermique, homogène, de longueur L, de section S et de conductivité thermique λ et sans échanges thermiques latéraux, relie le bolomètre à un thermostat de température T_b fixe.

Figure 1 - Schéma d'un bolomètre

I.1. Dans cette première partie, on étudie le comportement du bolomètre en régime stationnaire, à la température de fonctionnement $T = T_0$.

I.1.a) Exprimer la température $T(x)$ en tout point du barreau conducteur repéré par son abscisse x ; on prendra $T(0) = T_0$ et $T(L) = T_b$.

GPT-4 To answer question I.1.a, we need to express the temperature $T(x)$ in every point of the conductive bar, which is characterized by the abscissa x. We are given that $T(0) = T0$ and $T(L) = Tb$.

For a stationary regime, the heat equation for the one-dimensional heat conduction in the bar is:
$d^2T/dx^2 = 0$

Integrating once, we get:
$dT/dx = C_1$

Integrating a second time:
$T(x) = C_1x + C_2$

To determine the constants C_1 and C_2, we use the boundary conditions:
$T(0) = T0$, which gives $C_2 = T0$
$T(L) = Tb$, which gives $C_1 = (Tb - T0)/L$

Finally, the expression for $T(x)$ is:
$T(x) = (Tb - T0) * (x/L) + T0$
This represents a linear temperature profile along the conductive bar, with a slope of $(Tb - T0)/L$.

Table 15. Example prompt demonstrating GPT-4's visual input capability. The prompt consists of a question which requires understanding a physics problem with a diagram written in French and solving it using chain-of-thought prompting.

Figure 24: Challenging visual examples from OpenAI technique report [33] that requires scaling the visual understanding and reasoning capability.

However, there is a large gap in terms of scaling a given capability, for example, even the for visual reasoning capability that we have observed in LLaVA. Figure 24 shows two more visual examples from OpenAI technique report. To correctly answer the questions, it requires models to understand multiple high-resolution images and long sequence, as well we responding with domain knowledge. It requires much larger compute and more powerful language models, which are not available for most people.

In summary, we have presented the background and strong capabilities of large multimodal models, reviewed instruction tuning in LLMs, and showed how we can build a prototype such as LLaVA and minigpt4 using open-sourced resources. We also summarize and cateorized the most recent papers merged on this line of research to help thoese who are interested to gain the momentum to start the journey of LMM research.

To discuss the next steps to work on as a community, one sustainable suggestion can be that those with resource can continue focusing on the scaling success and study new emerging properties, while others focus on prototypes for new functionalities and evaluation, as well as developing techniques to reduce the compute barriers and thus allow more accessibility for larger model compute.

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References

[1] Jean-Baptiste Alayrac, Jeff Donahue, Pauline Luc, Antoine Miech, Iain Barr, Yana Hasson, Karel Lenc, Arthur Mensch, Katie Millican, Malcolm Reynolds, et al. Flamingo: a visual language model for few-shot learning. *arXiv preprint arXiv:2204.14198*, 2022. 5, 6, 17

[2] Anas Awadalla, Irena Gao, Joshua Gardner, Jack Hessel, Yusuf Hanafy, Wanrong Zhu, Kalyani Marathe, Yonatan Bitton, Samir Gadre, Jenia Jitsev, Simon Kornblith, Pang Wei Koh, Gabriel Ilharco, Mitchell Wortsman, and Ludwig Schmidt. Openflamingo, March 2023. 13, 18, 19

[3] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020. 5, 6

[4] Feilong Chen, Minglun Han, Haozhi Zhao, Qingyang Zhang, Jing Shi, Shuang Xu, and Bo Xu. X-llm: Bootstrapping advanced large language models by treating multi-modalities as foreign languages. *arXiv preprint arXiv:2305.04160*, 2023. 17

[5] Together Computer. Redpajama-data: An open source recipe to reproduce llama training dataset, 2023. 10

[6] Wenliang Dai, Junnan Li, Dongxu Li, Anthony Meng Huat Tiong, Junqi Zhao, Weisheng Wang, Boyang Li, Pascale Fung, and Steven Hoi. Instructblip: Towards general-purpose vision-language models with instruction tuning. *arXiv preprint arXiv:2305.06500*, 2023. 18

[7] Tim Dettmers, Artidoro Pagnoni, Ari Holtzman, and Luke Zettlemoyer. Qlora: Efficient finetuning of quantized llms. *arXiv preprint arXiv:2305.14314*, 2023. 19

[8] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805*, 2018. 6

[9] Danny Driess, Fei Xia, Mehdi SM Sajjadi, Corey Lynch, Aakanksha Chowdhery, Brian Ichter, Ayzaan Wahid, Jonathan Tompson, Quan Vuong, Tianhe Yu, et al. PaLM-E: An embodied multimodal language model. *arXiv preprint arXiv:2303.03378*, 2023. 17

[10] Peng Gao, Jiaming Han, Renrui Zhang, Ziyi Lin, Shijie Geng, Aojun Zhou, Wei Zhang, Pan Lu, Conghui He, Xiangyu Yue, et al. Llama-adapter v2: Parameter-efficient visual instruction model. *arXiv preprint arXiv:2304.15010*, 2023. 19

[11] Xinyang Geng and Hao Liu. Openllama: An open reproduction of llama, May 2023. 10

[12] Rohit Girdhar, Alaaeldin El-Nouby, Zhuang Liu, Mannat Singh, Kalyan Vasudev Alwala, Armand Joulin, and Ishan Misra. Imagebind: One embedding space to bind them all. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 15180–15190, 2023. 17

[13] Tao Gong, Chengqi Lyu, Shilong Zhang, Yudong Wang, Miao Zheng, Qian Zhao, Kuikun Liu, Wenwei Zhang, Ping Luo, and Kai Chen. Multimodal-gpt: A vision and language model for dialogue with humans. *arXiv preprint arXiv:2305.04790*, 2023. 18

[14] Arnav Gudibande, Eric Wallace, Charlie Snell, Xinyang Geng, Hao Liu, Pieter Abbeel, Sergey Levine, and Dawn Song. The false promise of imitating proprietary llms. *arXiv preprint arXiv:2305.15717*, 2023. 10

[15] Shaohan Huang, Li Dong, Wenhui Wang, Yaru Hao, Saksham Singhal, Shuming Ma, Tengchao Lv, Lei Cui, Owais Khan Mohammed, Qiang Liu, et al. Language is not all you need: Aligning perception with language models. *arXiv preprint arXiv:2302.14045*, 2023. 17

[16] Jing Yu Koh, Daniel Fried, and Ruslan Salakhutdinov. Generating images with multimodal language models. *arXiv preprint arXiv:2305.17216*, 2023. 17, 22

[17] Bo Li, Yuanhan Zhang, Liangyu Chen, Jinghao Wang, Fanyi Pu, Jingkang Yang, Chunyuan Li, and Ziwei Liu. Mimic-it: Multi-modal in-context instruction tuning. *arXiv preprint arXiv:2306.05425*, 2023. 19

[18] Bo Li, Yuanhan Zhang, Liangyu Chen, Jinghao Wang, Jingkang Yang, and Ziwei Liu. Otter: A multi-modal model with in-context instruction tuning. *arXiv preprint arXiv:2305.03726*, 2023. 18

[19] Chunyuan Li, Cliff Wong, Sheng Zhang, Naoto Usuyama, Haotian Liu, Jianwei Yang, Tristan Naumann, Hoifung Poon, and Jianfeng Gao. Llava-med: Training a large language-and-vision assistant for biomedicine in one day. *arXiv preprint arXiv:2306.00890*, 2023. 20, 21

[20] Junnan Li, Dongxu Li, Silvio Savarese, and Steven Hoi. Blip-2: Bootstrapping language-image pre-training with frozen image encoders and large language models. *arXiv preprint arXiv:2301.12597*, 2023. 4, 5, 13, 20

[21] KunChang Li, Yinan He, Yi Wang, Yizhuo Li, Wenhai Wang, Ping Luo, Yali Wang, Limin Wang, and Yu Qiao. Videochat: Chat-centric video understanding. *arXiv preprint arXiv:2305.06355*, 2023. 17

[22] Lei Li, Yuwei Yin, Shicheng Li, Liang Chen, Peiyi Wang, Shuhuai Ren, Mukai Li, Yazheng Yang, Jingjing Xu, Xu Sun, et al. M3it: A large-scale dataset towards multi-modal multilingual instruction tuning. *arXiv preprint arXiv:2306.04387*, 2023. 18

[23] Yifan Li, Yifan Du, Kun Zhou, Jinpeng Wang, Wayne Xin Zhao, and Ji-Rong Wen. Evaluating object hallucination in large vision-language models. *arXiv preprint arXiv:2305.10355*, 2023. 20

[24] Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *arXiv preprint arXiv:2304.08485*, 2023. 11, 12, 13, 14

[25] Yuliang Liu, Zhang Li, Hongliang Li, Wenwen Yu, Mingxin Huang, Dezhi Peng, Mingyu Liu, Mingrui Chen, Chunyuan Li, Lianwen Jin, et al. On the hidden mystery of ocr in large multimodal models. *arXiv preprint arXiv:2305.07895*, 2023. 20

[26] Pan Lu, Swaroop Mishra, Tanglin Xia, Liang Qiu, Kai-Wei Chang, Song-Chun Zhu, Oyvind Tafjord, Peter Clark, and Ashwin Kalyan. Learn to explain: Multimodal reasoning via thought chains for science question answering. *Advances in Neural Information Processing Systems*, 2022. 13

[27] Gen Luo, Yiyi Zhou, Tianhe Ren, Shengxin Chen, Xiaoshuai Sun, and Rongrong Ji. Cheap and quick: Efficient vision-language instruction tuning for large language models. *arXiv preprint arXiv:2305.15023*, 2023. 19

[28] Ruipu Luo, Ziwang Zhao, Min Yang, Junwei Dong, Minghui Qiu, Pengcheng Lu, Tao Wang, and Zhongyu Wei. Valley: Video assistant with large language model enhanced ability. *arXiv preprint arXiv:2306.07207*, 2023. 17

[29] Mark Mazumder, Colby Banbury, Xiaozhe Yao, Bojan Karlaš, William Gaviria Rojas, Sudnya Diamos, Greg Diamos, Lynn He, Douwe Kiela, David Jurado, et al. Dataperf: Benchmarks for data-centric ai development. *arXiv preprint arXiv:2207.10062*, 2022. 10

[30] Masoud Monajatipoor, Liunian Harold Li, Mozhdeh Rouhsedaghat, Lin F Yang, and Kai-Wei Chang. Metavl: Transferring in-context learning ability from language models to vision-language models. *arXiv preprint arXiv:2306.01311*, 2023. 18

[31] Yao Mu, Qinglong Zhang, Mengkang Hu, Wenhai Wang, Mingyu Ding, Jun Jin, Bin Wang, Jifeng Dai, Yu Qiao, and Ping Luo. Embodiedgpt: Vision-language pre-training via embodied chain of thought. *arXiv preprint arXiv:2305.15021*, 2023. 17

[32] OpenAI. ChatGPT. `https://openai.com/blog/chatgpt/`, 2022. 3, 9

[33] OpenAI. GPT-4 technical report. `https://arxiv.org/abs/2303.08774`, 2023. 3, 6, 9, 13, 14, 17, 22

[34] Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744, 2022. 7, 9, 18

[35] Guilherme Penedo, Quentin Malartic, Daniel Hesslow, Ruxandra Cojocaru, Alessandro Cappelli, Hamza Alobeidli, Baptiste Pannier, Ebtesam Almazrouei, and Julien Launay. The RefinedWeb dataset for Falcon LLM: outperforming curated corpora with web data, and web data only. *arXiv preprint arXiv:2306.01116*, 2023. 10

[36] Baolin Peng, Chunyuan Li, Pengcheng He, Michel Galley, and Jianfeng Gao. Instruction tuning with GPT-4. *arXiv preprint arXiv:2304.03277*, 2023. 9

[37] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. *arXiv preprint arXiv:2103.00020*, 2021. 12

[38] Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. Language models are unsupervised multitask learners. *OpenAI blog*, 2019. 6

[39] ShareGPT. `https://sharegpt.com/`, 2023. 9

[40] Piyush Sharma, Nan Ding, Sebastian Goodman, and Radu Soricut. Conceptual captions: A cleaned, hypernymed, image alt-text dataset for automatic image captioning. In *ACL*, 2018. 12

[41] Yixuan Su, Tian Lan, Huayang Li, Jialu Xu, Yan Wang, and Deng Cai. Pandagpt: One model to instruction-follow them all. *arXiv preprint arXiv:2305.16355*, 2023. 17

[42] Yuxuan Sun, Chenglu Zhu, Sunyi Zheng, Kai Zhang, Zhongyi Shui, Xiaoxuan Yu, Yizhi Zhao, Honglin Li, Yunlong Zhang, Ruojia Zhao, et al. Pathasst: Redefining pathology through generative foundation ai assistant for pathology. *arXiv preprint arXiv:2305.15072*, 2023. 21

[43] Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. `https://github.com/tatsu-lab/stanford_alpaca`, 2023. 9

[44] MosaicML NLP Team. Introducing mpt-7b: A new standard for open-source, ly usable llms, 2023. Accessed: 2023-03-28. 10

[45] Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023. 9, 19

[46] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *NeurIPS*, 2017. 4

[47] Vicuna. Vicuna: An open-source chatbot impressing GPT-4 with 90%* chatgpt quality. `https://vicuna.lmsys.org/`, 2023. 9, 10, 12

[48] Jianfeng Wang, Zhengyuan Yang, Xiaowei Hu, Linjie Li, Kevin Lin, Zhe Gan, Zicheng Liu, Ce Liu, and Lijuan Wang. Git: A generative image-to-text transformer for vision and language. *arXiv preprint arXiv:2205.14100*, 2022. 4, 5

[49] Wenhai Wang, Zhe Chen, Xiaokang Chen, Jiannan Wu, Xizhou Zhu, Gang Zeng, Ping Luo, Tong Lu, Jie Zhou, Yu Qiao, et al. VisionLLM: Large language model is also an open-ended decoder for vision-centric tasks. *arXiv preprint arXiv:2305.11175*, 2023. 17

[50] Yizhong Wang, Hamish Ivison, Pradeep Dasigi, Jack Hessel, Tushar Khot, Khyathi Raghavi Chandu, David Wadden, Kelsey MacMillan, Noah A Smith, Iz Beltagy, et al. How far can camels go? exploring the state of instruction tuning on open resources. *arXiv preprint arXiv:2306.04751*, 2023. 9

[51] Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language model with self generated instructions. *arXiv preprint arXiv:2212.10560*, 2022. 9

[52] Yizhong Wang, Swaroop Mishra, Pegah Alipoormolabashi, Yeganeh Kordi, Amirreza Mirzaei, Anjana Arunkumar, Arjun Ashok, Arut Selvan Dhanasekaran, Atharva Naik, David Stap, et al. Benchmarking generalization via in-context instructions on 1,600+ language tasks. *arXiv preprint arXiv:2204.07705*, 2022. 9, 18

[53] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Ed Chi, Quoc Le, and Denny Zhou. Chain of thought prompting elicits reasoning in large language models. *arXiv preprint arXiv:2201.11903*, 2022. 6

[54] Zhenxiang Xiao, Yuzhong Chen, Lu Zhang, Junjie Yao, Zihao Wu, Xiaowei Yu, Yi Pan, Lin Zhao, Chong Ma, Xinyu Liu, et al. Instruction-vit: Multi-modal prompts for instruction learning in vit. *arXiv preprint arXiv:2305.00201*, 2023. 18

[55] Xudong Xie, Ling Fu, Zhifei Zhang, Zhaowen Wang, and Xiang Bai. Toward understanding wordart: Corner-guided transformer for scene text recognition, 2022. 20

[56] Peng Xu, Wenqi Shao, Kaipeng Zhang, Peng Gao, Shuo Liu, Meng Lei, Fanqing Meng, Siyuan Huang, Yu Qiao, and Ping Luo. Lvlm-ehub: A comprehensive evaluation benchmark for large vision-language models. *arXiv preprint arXiv:2306.09265*, 2023. 20

[57] Zhiyang Xu, Ying Shen, and Lifu Huang. Multiinstruct: Improving multi-modal zero-shot learning via instruction tuning. *arXiv preprint arXiv:2212.10773*, 2022. 18

[58] Qinghao Ye, Haiyang Xu, Guohai Xu, Jiabo Ye, Ming Yan, Yiyang Zhou, Junyang Wang, Anwen Hu, Pengcheng Shi, Yaya Shi, et al. mplug-owl: Modularization empowers large language models with multimodality. *arXiv preprint arXiv:2304.14178*, 2023. 18

[59] Zhenfei Yin, Jiong Wang, Jianjian Cao, Zhelun Shi, Dingning Liu, Mukai Li, Lu Sheng, Lei Bai, Xiaoshui Huang, Zhiyong Wang, et al. Lamm: Language-assisted multi-modal instruction-tuning dataset, framework, and benchmark. *arXiv preprint arXiv:2306.06687*, 2023. 20

[60] Yuhang Zang, Wei Li, Jun Han, Kaiyang Zhou, and Chen Change Loy. Contextual object detection with multimodal large language models. *arXiv preprint arXiv:2305.18279*, 2023. 17

[61] Dong Zhang, Shimin Li, Xin Zhang, Jun Zhan, Pengyu Wang, Yaqian Zhou, and Xipeng Qiu. Speechgpt: Empowering large language models with intrinsic cross-modal conversational abilities. *arXiv preprint arXiv:2305.11000*, 2023. 17

[62] Hang Zhang, Xin Li, and Lidong Bing. Video-llama: An instruction-tuned audio-visual language model for video understanding. *arXiv preprint arXiv:2306.02858*, 2023. 17

[63] Xiaoman Zhang, Chaoyi Wu, Ziheng Zhao, Weixiong Lin, Ya Zhang, Yanfeng Wang, and Weidi Xie. Pmc-vqa: Visual instruction tuning for medical visual question answering. *arXiv preprint arXiv:2305.10415*, 2023. 21

[64] Yunqing Zhao, Tianyu Pang, Chao Du, Xiao Yang, Chongxuan Li, Ngai-Man Cheung, and Min Lin. On evaluating adversarial robustness of large vision-language models. *arXiv preprint arXiv:2305.16934*, 2023. 20

[65] Zijia Zhao, Longteng Guo, Tongtian Yue, Sihan Chen, Shuai Shao, Xinxin Zhu, Zehuan Yuan, and Jing Liu. Chatbridge: Bridging modalities with large language model as a language catalyst. *arXiv preprint arXiv:2305.16103*, 2023. 17

[66] Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models, 2023. 11

[67] Wanrong Zhu, Jack Hessel, Anas Awadalla, Samir Yitzhak Gadre, Jesse Dodge, Alex Fang, Youngjae Yu, Ludwig Schmidt, William Yang Wang, and Yejin Choi. Multimodal c4: An open, billion-scale corpus of images interleaved with text. *arXiv preprint arXiv:2304.06939*, 2023. 19