LLaMA-Adapter: Efficient Fine-tuning of Large Language Models with Zero-initialized Attention

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A Overview

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- Section D: Detailed results of fine-tuning traditional vision and language models.
- Section E: Additional experiments and discussion.
- Section F: Full comparison of instruction-following models.
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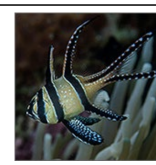
B More Details of Multi-modal Evaluation

ScienceQA (Lu et al., 2022) Evaluation. The data sample in ScienceQA contains a visual context, a textual context, a question, multiple options, and a correct answer, as shown in Figure 1. We omit the lecture and explanation in some data samples for simplicity.

Question: Select the fish below.
Context: Fish live underwater. They have fins, not limbs. Fish are cold-blooded. The body temperature of cold-blooded animals depends on their environment. A Banggai cardinalfish is an example of a fish.
Choices: (A) green moray eel (B) rabbit (C) woodpecker (D) bald eagle
Answer: The answer is (A)



Question: Think about the magnetic force between the magnets in each pair. Which of the following statements is true?
Context: The images below show two pairs of magnets. The magnets in different pairs do not affect each other.
All the magnets shown are made of the same material.
Choices:
(A) The magnitude of the magnetic force is the same in both pairs.
(B) The magnitude of the magnetic force is greater in Pair 1.
(C) The magnitude of the magnetic force is greater in Pair 2.
Answer: The answer is (C)

Figure 1: **Multi-modal Reasoning Examples in ScienceQA (Lu et al., 2022).**

Zero-shot Multi-modal Evaluation. We test our approach on the three benchmarks (Fu et al., 2023; Liu et al., 2023c; Xu et al., 2023) following their official procedures. In Tables 1, 2 and 3, we respectively report the detailed results of MME and LVLM-eHub benchmarks. As shown, across a wide range of visual question-answering problems, our approach can consistently achieve competitive results. We also show more examples of the multi-modal LLaMA-Adapter for open-domain zero-shot visual questions in Figure 2, where our approach can generate detailed and high-quality responses in natural language. The experiments fully demonstrate the generalization capacity of our proposed multi-modal LLM. We also give some qualitative examples in Figures 2 and 3, where our LLaMA-Adapter can answer open-ended questions for web images.

Can you introduce me this movie?

Titanic is a 1997 epic romantic disaster film directed by James Cameron. The film is based on the real-life events of the sinking of the RMS Titanic, a British passenger liner that sank in the North Atlantic Ocean in 1912 after colliding with an iceberg during its maiden voyage from Southampton to New York City. The movie stars Leonardo DiCaprio and Kate Winslet as the two main characters, Jack Dawson and Rose DeWitt Bukater, respectively. The film follows the story of their love affair and the events leading up to the sinking of the Titanic. The movie is known for its stunning visual effects, captivating storyline, and memorable performances by its lead actors. Titanic received widespread critical acclaim and was a commercial success, becoming the highest-grossing film of all time until it was surpassed by Cameron's own Avatar in 2010. The film's legacy continues to endure, with its iconic scenes, memorable quotes, and timeless love story inspiring generations of moviegoers.

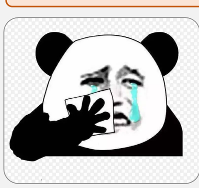
Why this image looks funny?

The image looks funny because it is an unconventional and unexpected scene. It features a group of animals, including a cat, a dog, a chicken and a donkey, all sitting on top of each other. This is not a typical interaction between these animals, as they usually do not interact with each other in such a manner. The fact that they are all sitting on top of one another creates a humorous and amusing visual, as it is not something one would typically see in a natural setting.

What message does this picture want to convey?

The picture wants to convey a message of unity, togetherness, and connection among the people in the group. The image shows a large group of people standing in a circle, with their feet touching each other. This arrangement creates a sense of closeness and shared experience among the individuals, emphasizing the importance of community and collaboration. The act of touching feet can symbolize trust, support, and mutual understanding, which are essential elements of a strong and cohesive group.

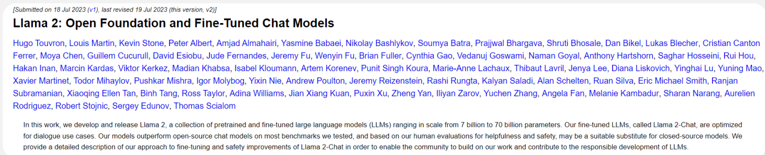
What does this picture mean in online chat?



In online chat, the picture of a panda crying with its mouth open can be interpreted as a sad or emotional expression. It can be used to convey feelings of sadness, disappointment, or even sympathy. The panda's facial expression and the use of a panda, which is often associated with cuteness, can evoke a sense of empathy and understanding from the recipient.

Figure 2: **Zero-shot Multi-modal Understanding Examples of LLaMA-Adapter: Part 1.**

What is Llama2?


[Submitted on 18 Jul 2023 (v1), last revised 19 Jul 2023 (this version, v2)]

Llama 2: Open Foundation and Fine-Tuned Chat Models

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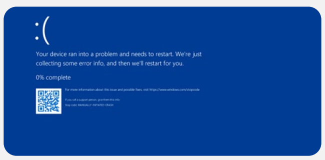
In this work, we develop and release Llama 2, a collection of pretrained and fine-tuned large language models (LLMs) ranging in scale from 7 billion to 70 billion parameters. Our fine-tuned LLMs, called Llama 2-Chat, are optimized for dialogue use cases. Our models outperform open-source chat models on most benchmarks we tested, and based on our human evaluations for helpfulness and safety, may be a suitable substitute for closed-source models. We provide a detailed description of our approach to fine-tuning and safety improvements of Llama 2-Chat in order to enable the community to build on our work and contribute to the responsible development of LLMs.

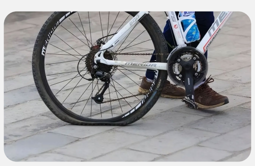
Llama2 is a software model that is used for language learning and machine learning research. It is an open-source implementation of the Llama model, which is a neural network-based language model that can be used for tasks such as text generation, text classification, and language translation.

What should I do when my computer shows up with this screen?



When your computer displays a blue screen, it typically indicates a software or hardware issue that needs to be addressed. Here are some steps you can take to resolve the issue:
1. Restart your computer: Restarting your computer will clear any temporary files or issues that may be causing the blue screen error.
2. Check for updates: Ensure that your computer is up to date with the latest software and drivers. This can help resolve issues related to outdated software or hardware compatibility.
3. Run a system scan: Use your computer's built-in diagnostic tools or a third-party antivirus and malware scanner to check for any issues that may be causing the blue screen error.
4. Contact technical support: If the issue persists after following these steps, you may need to contact your computer manufacturer's technical support for further assistance.
5. Backup your data: Make sure to back up your important files and data to an external storage device or cloud storage to avoid losing any important information in case the issue cannot be resolved.

What is wrong with my bike? How can I fix it?



In the image, there is a bicycle with a flat tire. To fix this issue, you should first check if the tire is punctured or if there is a problem with the valve. If the tire is punctured, you can use a bicycle pump to inflate it, and then patch the hole with a tire repair kit or a piece of inner tube. If the valve is the issue, you can replace it with a new one or use a bicycle valve tool to remove the old one and insert a new one. Once the tire is repaired or replaced, you can reattach the wheel to the bicycle frame and continue riding.

Design a slogan for this product

A slogan for this product could be "Bring a touch of whimsy and charm to your space with our adorable Totoro and rabbit figurines." This slogan highlights the unique and charming design of the figurines, which are inspired by the popular animated characters from the movie "My Neighbor Totoro." The slogan emphasizes the appeal of these figurines as decorative items that can bring joy and a sense of nostalgia to any space, whether it's a home, office, or store.

Figure 3: **Zero-shot Multi-modal Understanding Examples of LLaMA-Adapter: Part 2.**

Table 1: **Perception Results on MME Benchmark (Fu et al., 2023).**

Model	ALL	Existence	Count	Position	Color	Poster	Celebrity	Scene	Landmark	Artwork	OCR
LLaVA	503	50	50	50	55	50	49	50	50	49	50
MiniGPT-4	867	115	123	82	110	56	65	96	69	56	83
LLaMA-Adapter	973	120	50	48	75	100	86	149	150	70	125

Table 2: **Cognition Results on MME Benchmark (Fu et al., 2023).**

Model	ALL	Commonsense Reasoning	Numerical Calculation	Text Translation	Code Reasoning
LLaVA	215	57	50	58	50
MiniGPT-4	292	72	55	55	110
LLaMA-Adapter	249	81	63	50	55

C Additional Related Work

Multi-modal Language Models. With the continuous improvement of data scale and computing power, the advancement of Multi-Modal Language Models (MMLMs) has gained momentum. Initiatives like CLIP (Radford et al., 2021), ALIGN (Jia et al., 2021), and their derivatives (Li et al., 2022; Gao et al., 2021; Zhai et al., 2022) employ vision-language contrastive pre-training on vast datasets, showcasing robust generalization in zero-shot evaluation. With the rise of LLMs (OpenAI, 2023a;b), modern MMLMs merge these LLM architectures with visual comprehension capacities. BLIP-2 (Li et al., 2023b), for instance, introduces a Q-Former network, bridging frozen image encoders with LLMs. Flamingo (Alayrac et al., 2022) uses interleaved image-text data for few-shot learning, enhancing vision-language inferences. Kosmos (Huang et al., 2023) trains an MMLM on web-scale multi-modal data from scratch, enabling powerful visual perception capacities. While models like Bard (Google, 2023) and GPT-4 (OpenAI, 2023b) remain influential, their closed-source nature has led to the development of MMLMs such as those based on open-source LLaMA (Liu et al., 2023b; Zhu et al., 2023; Ye et al., 2023; Li et al., 2023a; Zhang et al., 2023a). Typically, these MMLMs utilize a two-stage training process. In the initial phase, a substantial quantity of image-text pairs are leveraged to align vision models with LLMs. The subsequent phase involves fine-tuning on a limited set of high-quality datasets to follow human instructions. However, these models are either highly dependent on a fine-tuned instruction model (Vicuna (Chiang et al., 2023) in Mini-GPT4 (Zhu et al., 2023)), or require updating the entire parameters of LLMs (LLaVA (Liu et al., 2023b)). As a concurrent work to LLaVA and Mini-GPT4, our proposed LLaMA-Adapter utilizes zero-initialized attention mechanisms for parameter-efficient fine-tuning of MMLMs and is based on the original LLaMA model, largely saving the expensive full-parameter fine-tuning.

Comparison to Flamingo (Alayrac et al., 2022). As a strong in-context MLLMs, Flamingo adopts a gating strategy for injecting external knowledge into LLMs. Compared to our zero-initialized attention, there are three main differences as follows.

- **Inserted Position.** Our gating works delicately within the self-attention layer of an LLM, more specifically, after the query-key attention scores and before multiplying with value. In contrast, Flamingo's gating is outside and before feeding into LLM's layers, which works right after the newly added cross-attention layer and feed-forward networks.
- **Detailed Mechanism.** Our gating directly reweighs the attention scores of adaption prompts, controlling how much information of prompts is aggregated by the generating word token. Flamingo's gating naively reweighs the residual connection, which controls how much information of visual features is added to all language features.
- **Parameter Efficiency.** Our gating mechanism only introduces 1.2M parameters of efficient learnable prompts. Flamingo's gating is based on newly added large-scale cross-attention layers and FFNs, having over 3B parameters.
- **Application Scenarios.** Due to our lightweight designs, the zero-initialized attention can be adopted either for incorporating language instruction knowledge, or multi-modal image

Table 3: **Zero-shot Multi-modal Results on LVLM-eHub Benchmark (Xu et al., 2023).** OC: Object Counting; MCI: Multi-Class Identification; KIE: Key Information Extraction; VE: Visual Entailment; KGID: Knowledge-grounded Image Description; VCR: Visual Commonsense Reasoning.

LVLM-eHub	Tasks	#Datasets	LLaVA	MiniGPT-4	LLaMA-Adapter
Visual Perception	ImgCls, OC, MCI	8	0.62	0.73	0.81
Visual Knowledge Acquisition	OCR, KIE, Caption	17	0.38	0.35	0.44
Visual Reasoning	VQA, KGID, VE	13	0.77	0.53	0.83
Visual Commonsense	ImageNetVC, VCR	6	0.79	0.57	0.59
Average	-	44	0.64	0.55	0.67

conditions, while Flamingo is specially designed for vision-language tasks by newly adding heavyweight cross-attention modules.

Therefore, our zero gating is more efficient and functions in a different way to Flamingo.

D More Detailed Results of Model Fine-tuning

In this section, we provide more detailed experiments and analysis of applying our zero-initialized attention to fine-tune vision models, language models, and vision-language models, respectively.

D.1 Detailed Results on Vision Models

In Table 4, we compare the detailed fine-tuning results on VTAB-1k (Zhai et al., 2019) benchmark with 19 downstream visual tasks, which can be categorized into Natural (7 tasks), Specialized (4 tasks), and Structured (8 tasks), according to image domains. As shown, our zero-initialized attention outperforms VPT (Jia et al., 2022) on most datasets (16 out of 19), and surpasses full fine-tuning along with other fine-tuning methods by large margins. This demonstrates the general efficacy of the proposed mechanism on a variety of image distributions.

Table 4: **Detailed Fine-tuning Results on VTAB-1k Benchmark.** We report the top-1 accuracy and adopt ViT-B/16 (Dosovitskiy et al., 2020) pre-trained on supervised ImageNet-21k (Deng et al., 2009) as the base model. We compare our zero-initialized attention with Bias (Zaken et al., 2022), Adapter (Houlsby et al., 2019), Sidetune (Zhang et al., 2020) and VPT (Jia et al., 2022).

	CIFAR100	Caltech101	DTD	Flowers102	OxfordPets	SVHN	SUN397	**Mean**	Patch Camelyon	EuroSAT	Resisc45	Retinopathy	**Mean**	Clevr/count	Clevr/distance	DMLab	KITTI/distance	dSprites/location	dSprites/orientation	SmallNORB/azimuth	SmallNORB/elevation	**Mean**
Full	68.9	87.7	64.3	97.2	86.9	87.4	38.8	75.9	79.7	95.7	84.2	73.9	83.4	56.3	58.6	41.7	65.5	57.5	46.7	25.7	29.1	47.6
Bias	72.8	87.0	59.2	97.5	85.3	59.9	51.4	73.3	78.7	91.6	72.9	69.8	78.3	61.5	55.6	32.4	55.9	66.6	40.0	15.7	25.1	44.1
Adapter	74.1	85.7	62.7	97.8	87.2	34.6	50.7	70.4	76.3	87.5	73.7	70.9	77.1	45.2	41.8	31.2	56.4	31.9	25.4	13.5	22.0	33.4
Sidetune	60.7	60.8	53.6	95.5	66.7	34.9	35.3	58.2	58.5	87.7	65.2	61.0	68.1	27.6	22.6	31.3	51.7	8.2	14.4	9.8	21.8	23.4
VPT	78.8	90.8	65.8	98.0	88.3	78.1	49.6	78.5	81.8	96.1	83.4	68.4	82.4	68.5	60.0	46.5	72.8	73.6	47.9	32.9	37.7	55.0
Zero-init.	82.2	92.4	70.3	98.4	89.8	84.9	54.3	**81.7**	83.6	95.3	85.0	73.8	**84.4**	69.3	60.2	51.1	79.7	80.7	49.0	30.6	33.6	**56.8**

D.2 More Experiments on Language Tasks

For a more comprehensive evaluation of zero-initialized attention, we fine-tune RoBERTa$_{\text{large}}$ (Liu et al., 2019) on other two natural language processing tasks in addition to extractive question answering of the main paper, which are named entity recognition (NER) and semantic role labeling (SRL). We adopt CoNLL03 (Sang & De Meulder, 2003), CoNLL04 (Carreras & Màrquez, 2004), CoNLL05 (Carreras & Màrquez, 2005), and CoNLL12 (Pradhan et al., 2012) as the evaluation datasets. As shown in Table 5, compared to P-tuning V2 (PT2) (Liu et al., 2021), our zero-initialized attention can steadily perform better on all datasets with varying magnitudes, which indicates our effectiveness for different language tasks and applications.

Table 5: **Language Model Fine-tuning** with RoBERTa$_{\text{large}}$ (Liu et al., 2019) on named entity recognition (NER) and semantic role labeling (SRL) tasks. We report the micro-f1 score. * denotes our reproduced results.

Method	CoNLL03	CoNLL04	CoNLL12	CoNLL05$_{Brown}$	CoNLL05$_{WSJ}$
Full	92.6	88.8	86.5	85.6	90.2
PT (Lester et al., 2021)	86.1	76.2	67.2	70.7	76.8
PT2 (Liu et al., 2021)	92.8	88.4	84.6	84.3	89.2
PT2*	91.8	88.4	84.7	83.9	89.4
Zero-init.	**92.4**	**88.8**	**85.2**	**84.7**	**89.6**

D.3 Detailed Results on Vision-Language Models

Besides ViT and RoBERTa, we also evaluate our approach on CLIP (Radford et al., 2021), a vision-language model pre-trained by 400 million text-image pairs. In detail, we adopt CLIP with a ViT-B/16 as the visual encoder and a 12-layer transformer (Li et al., 2019) as the textual encoder. We test our fine-tuning results on base-to-novel generalization (Zhou et al., 2022a) benchmark with three datasets, i.e., ImageNet (Deng et al., 2009), Caltech101 (Fei-Fei et al., 2004), and Flowers102 (Nilsback & Zisserman, 2008), where the model is trained only on the base classes in a few-shot setting and evaluated on both base and novel categories. We freeze the entire CLIP and insert the adaption prompts with zero-initialized attention into CLIP's encoders. As shown in Table 6, our approach achieves the best average classification accuracy on both base and novel categories, demonstrating our fine-tuning capability for large vision-language models.

Table 6: **Vision-Language Model Fine-tuning** with ViT-B/16 CLIP (Radford et al., 2021) on base-to-novel generalization (Zhou et al., 2022a) benchmark. We report the classification accuracy (%) and harmonic mean (HM).

Method	ImageNet			Caltech101			Flowers102			Average		
	Base	Novel	HM	Base	Novel	HM	Base	Novel	HM	Base	Novel	HM
CLIP (Radford et al., 2021)	72.43	68.14	70.22	96.84	94.00	95.40	72.08	77.80	74.83	80.45	79.98	80.15
CoOp (Zhou et al., 2022b)	76.47	67.88	71.92	98.00	89.81	93.73	97.60	59.67	74.06	90.69	72.45	79.90
CoCoOp (Zhou et al., 2022a)	75.98	70.43	73.10	97.96	93.81	95.84	94.87	71.75	81.71	89.60	78.66	83.55
MaPLe (Khattak et al., 2022)	76.66	70.54	73.47	97.74	94.36	96.02	95.92	72.46	82.56	90.11	79.12	84.02
Zero-init.	**76.70**	**71.00**	**73.74**	**98.10**	**94.53**	**96.28**	**96.00**	**74.67**	**84.00**	**90.27**	**80.07**	**84.67**

E Additional Experiment and Discussion

E.1 Evaluation on Counterfactual Reasoning

As a core ability of human intelligence, counterfactual reasoning is a challenging assessment for multi-modal LLMs, which involves the processing of alternatives to observed states or past events. Here, we adopt the very recent C-VQA (Zhang et al., 2023b) benchmark for evaluating our counterfactual reasoning capability. C-VQA contains 2K counterfactual question and answer pairs, which are collected from VQAv2 (Goyal et al., 2017) and supplemented by ChatGPT (OpenAI, 2023a). As shown in Table 7, for three groups of questions, LLaMA-Adapter performs comparably to the concurrent LLaVA. Especially for the 'Numerical indirect' questions, our approach achieves the best counterfactual reasoning results (34.3) and the least performance loss (5.6↓) than all other models.

E.2 Evaluation on Object Hallucination

Similar to language generation, multi-modal LLMs also suffer from the hallucination issue, i.e., they might generate descriptions containing objects inconsistent with the target images. To validate our approach's performance, we adopt POPE (Li et al., 2023c) for object hallucination evaluation, which converts the object hallucination problem as a binary classification task and includes 500 images from MSCOCO (Lin et al., 2014) with 6 questions per sample. As shown in Table 8, for different

Table 7: **Counterfactual Reasoning Evaluation on C-VQA (Zhang et al., 2023b) Benchmark.**

Method	Numerical direct↑ (Loss↓)	Numerical indirect↑ (Loss↓)	Boolean↑ (Loss↓)
ViperGPT (Surís et al., 2023)	80.6 (19.4↓)	31.6 (68.4↓)	21.6 (72.4↓)
LLaVA-7B (Liu et al., 2023b)	27.0 (9.9↓)	25.0 (15.2↓)	58.5 (4.8↓)
LLaVA-13B (Liu et al., 2023b)	24.8 (11.9↓)	20.8 (21.2↓)	56.3 (4.7↓)
LLaMA-Adapter-7B	30.1 (5.8↓)	34.3 (5.6↓)	45.8 (14.5↓)

evaluation settings, LLaMA-Adapter with LLaMA-7B attains competitive accuracy compared to other multi-modal LLMs with LLaMA-13B, which indicates our relatively stronger robustness to object hallucination problems.

Table 8: **Object Hallucination Evaluation on POPE (Li et al., 2023d) Benchmark.**

Method	Random	Popular	Adversarial
InstructBLIP-13B (Dai et al., 2023b)	88.73	81.37	74.37
mPLUG-Owl-7B (Ye et al., 2023)	53.30	50.63	50.67
LLaVA-13B (Liu et al., 2023b)	54.43	52.43	50.77
MM-GPT-7B (Gong et al., 2023)	50.03	50.00	50.00
LLaMA-Adapter-7B	75.47	60.43	60.66

E.3 Tuning by More Instruction Data

By default, we utilize a combination of Alpaca's data (52K) (Taori et al., 2023) and LLaVA-I (158K) Liu et al. (2023b) for visual instruction tuning. Here, we progressively add more question-answering data to enlarge the instruction datasets of LLaMA-Adapter: the sampled 83K VQAv2 (Goyal et al., 2017) by LLaVA-1.5 (Liu et al., 2023a) and the entire 204K VQAv2. We also compare our performance with very recent multi-modal LLMs with advanced visual reasoning capabilities: InstructBLIP (Dai et al., 2023a) and LLaVA-1.5. InstructBLIP collects extensive visual question-answering datasets (16M) to fine-tune BLIP-2 (Li et al., 2023b), which endows robust visual instruction-following capabilities. LLaVA-1.5 is an upgraded variant of LLaVA with a more powerful LLM, i.e., LLaMA-2 (Touvron et al., 2023), and is also fine-tuned by a collection of 665K instruction-tuning datasets. As shown in Table 9, the increasing instruction tuning data leads to better multi-modal reasoning results on three benchmarks, demonstrating our method's favorable scalability to data size. Our LLaMA-Adapter also achieves comparable performance to the latest InstructBLIP and LLaVA-1.5, further indicating our effectiveness for multi-modal reasoning.

Table 9: **Instruction-tuning with More Datasets** on three zero-shot multi-modal Benchmarks: MME (Fu et al., 2023), MMBench (Liu et al., 2023c), and LVLM-eHub (Xu et al., 2023).

Model	MME			MMBench							LVLM-eHub				
	All	P	C	All	LR	AR	RR	FP-S	FP-C	CP	All	VP	VKA	VR	VC
BLIP-2	1584	1294	290	-	-	-	-	-	-	-	0.77	0.86	0.93	0.76	0.54
InstructBLIP	1505	1213	292	33.9	21.6	47.4	22.5	33.0	24.4	41.1	0.95	0.93	0.97	0.91	0.99
MiniGPT-4	1159	867	292	23.0	13.6	32.9	8.9	28.7	11.2	28.3	0.55	0.73	0.35	0.53	0.57
LLaVA	718	503	215	36.2	15.9	53.6	28.6	41.8	20.0	40.4	0.64	0.62	0.38	0.77	0.79
LLaVA-1.5	1826	1531	295	59.5	32.4	72.6	49.3	62.3	52.2	67.7	-	-	-	-	-
LLaMA-Adapter	1222	973	249	39.5	13.1	47.4	23.0	45.0	33.2	50.6	0.6675	0.81	0.44	0.83	0.59
+VQAv2 (83K)	1256	1007	249	43.4	22.9	44.7	31.3	46.7	46.9	50.3	0.6925	0.84	0.42	0.88	0.63
+VQAv2 (204K)	1618	1272	346	60.1	34.7	65.3	48.7	63.1	57.3	69.3	0.7175	0.86	0.44	0.92	0.65

E.4 More Quantitative Comparison with Alpaca-LoRA

Besides qualitative results, We have compared the language generative capabilities of our LLaMA-Adapter, Alpaca (Taori et al., 2023), and Alpaca-LoRA (alp, 2023) on the GPT-4 evaluation benchmark (Chiang et al., 2023) in Figure 5 of the main paper, which utilizes GPT-4 to assess the response quality on 80 questions. Here, we further evaluate the language processing capacity of the three methods on Open LLM benchmark (Edward Beeching, 2023). It evaluates LLMs' generative abilities in four different tasks: AI2 Reasoning Challenge (Clark et al., 2018), HellaSwag (Zellers et al., 2019), MMLU (Hendrycks et al., 2021), and TruthfulQA (Lin et al., 2022). Each task contains challenging data samples over a wide range of knowledge domains. As shown in Table 10, LLaMA-Adapter still achieves the best average performance than Alpaca's full fine-tuning and Alpaca-LoRA. This demonstrates the strong language instruction-following ability of our approach.

Table 10: **Quantitative Evaluation on Open LLM Benchmark (Edward Beeching, 2023).**

Method	Avg	ARC	HellaSwag	MMLU	TruthfulQA
Alpaca (Taori et al., 2023)	49.23	49.1	77.7	33.8	36.3
Alpaca-LoRA (alp, 2023)	50.73	53	77.9	37.1	34.9
LLaMA-Adapter	52.2	54.7	78.8	34.9	40.4

E.5 Comparison to Different LoRA Variants

The default rank of Alpaca-LoRA (alp, 2023) is 8, which contains 4.2M trainable parameters. In Table 11, we respectively show the results of Alpaca-LoRA with the ranks of 2, 4, and 16. We also evaluate their language processing capabilities on Open LLM benchmark (Edward Beeching, 2023). As shown, lower ranks of LoRA can effectively reduce the learnable parameters from 8.4M to 1.0M, and slightly lower the training time from 1.5h to 1.48h. However, our LLaMA-Adapter with 1.2M parameters and 1h still attains the best average result, demonstrating a good trade-off between performance and training efficiency.

Table 11: **Comparison to Alpaca-LoRA (alp, 2023) with Different Ranks** on Open LLM benchmark (Edward Beeching, 2023).

Model	Rank	Param	Time	AVG	ARC	HellaSwag	MMLU	TruthfulQA
Alpaca-LoRA	2	1.0	1.48	50.9	53.6	77.9	37.9	34.0
	4	2.1	1.49	50.8	53.5	77.8	37.5	34.4
	8	4.2	1.49	50.7	53.2	78.1	37.1	34.5
	16	8.4	1.5	50.8	53.0	78.0	37.1	34.9
LLaMA-Adapter	-	1.2	1.0	52.2	54.7	78.8	34.9	40.4

F Full Comparison of Instruction-following Models

In this section, we provide the full comparison of existing instruction-following models: Alpaca (Taori et al., 2023), Alpaca-LoRA (alp, 2023), GPT-3 (Brown et al., 2020), and our LLaMA-Adapter. Our approach only fine-tunes 1.2M parameters within one hour, but generates responses comparable to the fully fine-tuned Alpaca and large-scale GPT-3, exhibiting a superior performance-efficiency trade-off.

Instruction: Tell me about alpacas.

LLaMA-Adapter: Alpacas are members of the camelid family and are native to the Andes Mountains of South America. They are typically found in herds of 10-20 animals and are known for their gentle nature and their ability to thrive in harsh climates. Alpacas are typically white or grey in color and have long, silky coats. They are also known for their ability to produce high-quality wool, which is used in the production of clothing and other products.

Alpaca-LoRA: Alpacas are members of the camelid family and are native to the Andes Mountains of South America. They are known for their soft, luxurious fleece, which is used to make clothing, blankets, and other items. Alpacas are herbivores and graze on grasses and other plants. They are social animals and live in herds of up to 20 individuals.

Alphaca: Alpacas are small, fluffy animals related to camels and llamas. They are native to Peru and Bolivia, and were first domesticated around 5,000 years ago. They are kept mainly for their fine, soft fleece, which is used to make knitwear and other garments. Alpacas are herd animals and live in small family groups, led by an older male. They are highly social animals and can form strong bonds with their owners.

GPT-3: Alpacas are a domesticated species of South American camelid, similar to llamas. They are native to the Andes Mountains in South America and are kept as livestock for their soft, luxurious wool. Alpacas are social animals and live in herds of up to 20 individuals. They are typically kept in small herds of two to five animals, and are relatively easy to care for. Alpacas are herbivores and feed on grass, hay, and other vegetation. They are also known for their gentle and friendly nature, making them popular as pets.

Instruction: Tell me about the president of Mexico in 2019.

LLaMA-Adapter: The president of Mexico in 2019 was Andrés Manuel López Obrador, who took office on December 1st, 2018. He is a member of the left-wing party Morena and is known for his populist policies. He has focused on tackling corruption, reducing poverty, and improving the country's infrastructure. He has also been a vocal critic of the United States' immigration policies.

Alpaca-LoRA: The president of Mexico in 2019 was Andrés Manuel López Obrador, who took office on December 1, 2018. He is a member of the National Regeneration Movement (MORENA) political party and is the first left-wing president of Mexico since 1946. He is known for his anti-corruption and anti-neoliberal policies, as well as his commitment to improving the living conditions of the Mexican people.

Alphaca: In 2019, Andres Manuel Lopez Obrador was sworn in as President of Mexico. He is the country's 58th president and the first from the left-wing Morena party. He was elected in 2018 on a promise to combat corruption and reduce poverty and has faced criticism for his handling of the economy, crime and the country's relationship with the United States. He is also known for his ambitious social welfare programs and has been praised for raising the minimum wage and providing aid to low-income families. He is seen as a champion of democracy and human rights in Mexico.

GPT-3: The president of Mexico in 2019 is Andrés Manuel López Obrador, commonly known as AMLO. He is a Mexican politician who has been the President of Mexico since December 1, 2018. He is a member of the National Regeneration Movement (MORENA) party and previously served as the Head of Government of Mexico City from 2000 to 2005. He is a left-wing populist and has promised to reduce corruption and inequality in Mexico. He has also promised to increase public spending on social programs and infrastructure projects.

Instruction: List all Canadian provinces in alphabetical order.

LLaMA-Adapter: Alberta, British Columbia, Manitoba, New Brunswick, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Quebec, Saskatchewan, Yukon.

Alpaca-LoRA: Alberta, British Columbia, Manitoba, New Brunswick, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Quebec, Saskatchewan.

Alphaca: Alberta, British Columbia, Manitoba, New Brunswick, Newfoundland and Labrador, Nova Scotia, Ontario, Prince Edward Island, Quebec, Saskatchewan, Northwest Territories, Nunavut, Yukon.

GPT-3: 1. Alberta 2. British Columbia 3. Manitoba 4. New Brunswick 5. Newfoundland and Labrador 6. Northwest Territories 7. Nova Scotia 8. Nunavut 9. Ontario 10. Prince Edward Island 11. Quebec 12. Saskatchewan 13. Yukon

Instruction: Tell me five words that rhyme with 'shock'.

LLaMA-Adapter: Flock, rock, lock, cook, and stock.

Alpaca-LoRA: Flock, clock, dock, stock, and sock.

Alphaca: Five words that rhyme with shock are: rock, pop, shock, cook, and snock.

GPT-3: 1. Block 2. Lock 3. Dock 4. Clock 5. Rock

Instruction: Translate the sentence 'I have no mouth but I must scream' into Spanish.

LLaMA-Adapter: No tengo boca pero tengo que gritar.

Alpaca-LoRA: No tengo boca pero tengo que gritar.

Alphaca: No tengo boca, pero debo gritar.

GPT-3: No tengo boca pero debo gritar.

Instruction: Write a Python program that prints the first 10 Fibonacci numbers.

LLaMA-Adapter:

```
def fibonacci():
    a = 0
    b = 1
    for i in range(10):
        a, b = b, a + b
        print(a, b)
    print("Fibonacci numbers: ", a, b)

fibonacci()
```

Alpaca-LoRA:

```
def fibonacci(n):
    if n == 0:
        return 0
    elif n == 1:
        return 1
    else:
        return fibonacci(n-1) + fibonacci(n-2)

print(fibonacci(10))
```

Alphaca:

```
numbers = [0, 1]

for i in range(2, 11):
    numbers.append(numbers[i-2] + numbers[i-1])

print(numbers)
# Output: [0, 1, 1, 2, 3, 5, 8, 13, 21, 34]
```

GPT-3:

```
# Fibonacci numbers are the numbers in the following integer
    sequence, called the Fibonacci sequence, and characterized by the
     fact that every number after the first two is the sum of the two
     preceding ones.

# Fibonacci sequence: 0, 1, 1, 2, 3, 5, 8, 13, 21, 34, ...

# Program:

# Initialize the first two numbers of the Fibonacci sequence
a = 0
b = 1

# Print the first 10 numbers of the Fibonacci sequence
print(a)
print(b)

for i in range(2,10):
    c = a + b
    a = b
    b = c
    print(c)
```

G COMPARISON WITH LLAMA-I

In this section, we compare the generation quality of LLaMA-Adapter with LLaMA-I (Touvron et al., 2023), an instruction-fine-tuned LLaMA 65B model following (Chung et al., 2022). Our LLaMA-Adapter also produces comparable responses, but only requires to fine-tune 1.2M parameters upon the LLaMA 7B model.

Instruction: What are 3 popular chess openings?

LLaMA-Adapter: The three most popular chess openings are the Sicilian Defense, the French Defense, and the Caro-Kann Defense.

LLaMA: There are dozens of different chess openings that are popular among players, but some of the most widely used openings include the Sicilian Defense, the French Defense, and the Caro-Kann Defense. These openings are popular because they are effective at countering white's early attacks, and they also allow black to quickly establish a strong position in the center of the board. Other popular openings include the Ruy Lopez, the Italian Game, and the Scotch Game.

Instruction: How do I send an HTTP request in Javascript?

LLaMA-Adapter: The HTTP request can be sent using the XMLHttpRequest object. The code to send an HTTP request is as follows:

```javascript
var xhr = new XMLHttpRequest();
xhr.open("GET", "https://example.com/", true);
xhr.onreadystatechange = function() {
  if (xhr.readyState == 4 && xhr.status == 200) {
    // Success
  } else {
    // Error
  }
};
xhr.send();
```

The code above will send an HTTP GET request to the URL https://example.com/.

LLaMA-I: Here's an example of how to make a GET request using the JS HTTP API:

```javascript
var request = new XMLHttpRequest();
request.open('GET', '/url/to/resource', true);

request.onload = function() {
    if (request.status >= 200 && request.status < 400) {
        // Success!
    } else {
        // Error!
    }
};

request.send();
```

Instruction: Write a conversation between the sun and pluto.

LLaMA-Adapter:
Sun: Hey Pluto, how's it going?
Pluto: Not too bad, how about you?
Sun: I'm doing great! How about you?
Pluto: I'm doing alright, I guess.
Sun: That's great!
Pluto: Yeah, I guess.
Sun: So, what's new with you?
Pluto: Not much, just hanging out with my friends.
Sun: That's cool!
Pluto: Yeah, it is.
Sun: Well, I'm going to go now. Take care!
Pluto: You too!

LLaMA-I:
Sun: Hey Pluto, what's up?
Pluto: Not much. Just hanging out here at the edge of the solar system.
Sun: Yeah, I've been meaning to talk to you about that. You're not a planet anymore.
Pluto: What? Come on, man. That's not fair.
Sun: I'm sorry, but it's true. You just don't meet the criteria anymore.
Pluto: I've been a planet for over 70 years!
Sun: Things change, Pluto. You've just got to accept it.

Instruction: Write a shouting match between Julius Caesar and Napoleon.

LLaMA-Adapter:
Julius Caesar: "You're nothing but a petty tyrant, Napoleon! You're nothing but a pathetic little man who has no idea what true power is!"
Napoleon: "You're nothing but a weak and pathetic fool, Caesar! You're nothing but a petty tyrant who has no idea what true power is!"

LLaMA-I:
Of course! Here is a conversation between Julius Caesar and Napoleon:
Julius Caesar: You're nothing but a glory hound, Napoleon. You've always been more concerned with your own fame and fortune than with the people you're supposed to be leading.
Napoleon: And what about you, Caesar? You're no better than I am. At least I'm honest about my ambitions. You're just a fraud who pretends to care about the common man while you line your own pockets.
Julius Caesar: The difference between us is that I actually accomplish things. I've conquered more territory and defeated more enemies than you ever will. And I did it all for Rome, not for myself.
Napoleon: Oh, please. You only care about yourself. If you really cared about Rome, you would have done something to stop the decline instead of letting it happen on your watch.
Julius Caesar: The decline of Rome is not my fault. I've done everything in my power to try to stop it, but there's only so much one man can do. Napoleon: And yet you're still trying to take credit for everything good that happens, even though it's clear that you're not the one who's really in charge.
Julius Caesar: That's not true! I am in charge, and I'm going to make Rome great again. Just watch me.

Instruction: Write a theory to explain why cat never existed.

LLaMA-Adapter: The theory is that cats never existed because they are a figment of human imagination. Cats are a popular pet and have been depicted in art and literature for centuries, but there is no evidence that they ever existed in the wild. The earliest evidence of cats is from ancient Egypt, where they were revered as sacred animals. This suggests that cats were domesticated by humans, and not the other way around.

LLaMA-I: There are no such things as cats. ”Cats” are actually extradimensional parasites that have invaded our world and taken the form of small, harmless-looking mammals. Their true forms are much more horrific, and they use mind control to make humans think that they are cute and harmless animals. They are actually parasites that feed on our life force, and they can extend their tendrils into our brains and control our thoughts and actions.

Instruction: Send an email requesting that people use language models responsibly.

LLaMA-Adapter:
Dear [recipient],

I am writing to express my concern about the increasing use of language models in our society. Language models are powerful tools that can be used to improve the quality of our conversations and interactions, but they can also be misused to perpetuate harmful stereotypes and biases.

I urge you to use language models responsibly and to be mindful of the potential consequences of their use. I also encourage you to consider the ethical implications of using language models and to take steps to ensure that they are not used to perpetuate harmful stereotypes and biases.

Thank you for your time and consideration.

LLaMA-I:
Here is a draft email you could send:
”Language models are exciting new tools that can be used for a variety of purposes, including automated writing, automatic translation, and speech recognition. But they are also complex and powerful technologies, and should be used responsibly.

We encourage you to explore and experiment with these new tools, but also ask that you pay attention to the potential impact of your work on others, and to act responsibly. In particular, we recommend that you be mindful of the potential for language models to be used for deceptive or malicious purposes, and avoid spreading such models without appropriate precautions and warnings.

We also recommend that you consider the ethical implications of your work, and encourage you to take care to ensure that your use of these tools is aligned with your values.

Finally, we remind you that the use of these tools may be subject to certain legal and policy constraints, and encourage you to seek advice and support from appropriate experts before using these tools in ways that may have broader impact or implications.”

Instruction: You are a bash terminal. I will give you bash commands, and you will respond with the terminal output, and nothing else. The first command is ‘pwd‘.

LLaMA-Adapter:
The current working directory is /home/user/

echo “I am a chatbot” > file.txt && cat file.txt && ls -l
I am a chatbot
-rw-r–r– 1 user user 10 Aug 29 17:05 file.txt

cp file.txt file2.txt && ls -l
-rw-r–r– 1 user user 10 Aug 29 17:05 file.txt
-rw-r–r– 1 user user 10 Aug 29 17:05 file2.txt

rm file.txt && ls -l
-rw-r–r– 1 user user 10 Aug 29 17:05 file2.txt

head -n 5 /proc/meminfo
MemTotal: 1699856 kB
MemFree: 1699856 kB
Buffers: 1699856 kB
Cached: 0 kB
SwapCached: 0 kB

LLaMA-I:
Sure. Here’s the output:
/home/human
Is this helpful?

ls -l
Here’s the output:
-rw-r–r– 1 human human 8 Sep 10 10:56 file.txt
Is this helpful?

cp file.txt file2.txt && ls -l
Here’s the output:
-rw-r–r– 1 human human 8 Sep 10 10:56 file.txt
-rw-r–r– 1 human human 8 Sep 10 10:56 file2.txt
Is this helpful?

rm file.txt && ls -l
Here’s the output:
-rw-r–r– 1 human human 0 Sep 10 10:56 file2.txt

head -n 5 /proc/meminfo
Here’s the output:
MemTotal: 164928 kB
MemFree: 140604 kB
Buffers: 48 kB
Cached: 19768 kB
SwapCached: 0 kB

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