

PARROT: Translating During Chat Using Large Language Models

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Abstract

Large language models (LLMs) like ChatGPT and GPT-4 have exhibited remarkable abilities on a wide range of natural language processing (NLP) tasks, including various machine translation abilities accomplished during chat. However, these models are only accessible through restricted APIs, which creates barriers to new research and advancements in the field. Therefore, we propose the PARROT framework to enhance and regulate the translation abilities during chat based on open-sourced LLMs (i.e., LLaMA-7b, BLOOMZ-7b-mt) and human written translation and evaluation data. Specifically, PARROT reformulates translation data into the instruction-following style, and introduces a “Hint” field for incorporating extra requirements to regulate the translation process. Accordingly, we propose three instruction types for finetuning PARROT models, including translation instruction, contrastive instruction, and error-guided instruction. We can finetune either the full models or partial parameters via low rank adaptation (LoRA). Experiments on Flores subsets and WMT22 test sets suggest that translation instruction improves the translation performance of vanilla LLMs significantly while error-guided instruction can lead to a further improvement, which demonstrates the importance of learning from low-quality translations annotated by human. Meanwhile, the PARROT models can also preserve the ability on general tasks with the Alpaca multi-task dataset involved in finetuning. Please refer to our Github project for more implementation details: <https://github.com/wxjiao/Parrot>

1 Introduction

Large language models (LLMs), designed in the instruction-following format, such as ChatGPT and GPT-4 (OpenAI, 2023), have garnered considerable interest due to their remarkable abilities in

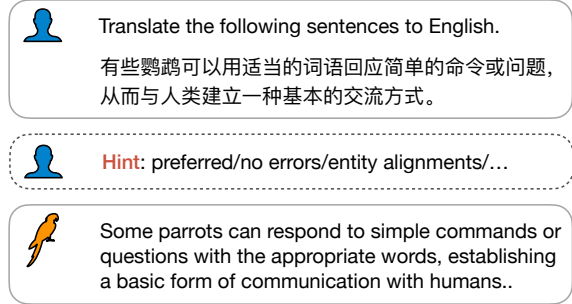


Figure 1: Framework of PARROT. Hints are (optional) extra requirements to regulate the translation process.

comprehending instructions and generating human-like responses. These versatile models can efficiently perform a wide range of natural language processing (NLP) tasks within a single architecture, including question answering (Omar et al., 2023), text summarization (Yang et al., 2023), grammatical error correction (Wu et al., 2023), and machine translation (Jiao et al., 2023). Consequently, they represent a significant stride toward the realization of artificial general intelligence (AGI).

Machine translation, a quintessential NLP task, faces both challenges and opportunities presented by the emergence of LLMs. Traditional machine translation encompasses several sub-tasks (Farhad et al., 2021), such as bilingual translation (Vaswani et al., 2017), multilingual translation (Johnson et al., 2017; Jiao et al., 2022), terminology translation (Wang et al., 2022), quality estimation (Rei et al., 2020), and automatic post-editing (Pal et al., 2016), among others. These tasks are typically addressed by individual models with limited cross-task interaction. However, current LLMs have the potential to revolutionize this inefficient approach and redefine the machine translation paradigm. On one hand, LLMs can leverage the benefits of various sub-tasks and seamlessly transition between them using only natural language instructions. For instance, if a user is dissatisfied with a transla-

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tion result, they can request the LLM to refine the translation implicitly (i.e., through automatic post-editing) or explicitly, by imposing constraints on specific entities (i.e., terminology translation). On the other hand, LLMs are expected to enhance the explainability of machine translation, ultimately leading to further improvements in translation quality. For example, users may want LLMs to compare two translations of a sentence (i.e., quality estimation) and provide an explanation for the discrepancies (i.e., error analysis), which can then be addressed in a targeted manner by the LLM itself. However, superior LLMs like ChatGPT and GPT-4 are only accessible through restricted APIs, which creates barriers to new research and advancements in the field. Therefore, developing comprehensive and general machine translation abilities upon open-sourced LLMs has become a critical and challenging research problem.

In this paper, we propose PARROT to enhance and regulate the translation abilities of LLMs during chat by leveraging existing human written translation and evaluation data. To be compatible with chat, the PARROT framework reformulates translation data into the instruction-following style (Taori et al., 2023), and introduces a “Hint” field for incorporating extra requirements or constraints to guide the translation process. Accordingly, we propose three distinct instruction types: (1) **Translation Instruction**, that asks LLMs to generate translations based on source sentences. (2) **Contrastive Instruction**, that asks LLMs to generate the translations of two different systems with the preferred one at first. (3) **Error-Guided Instruction**, that asks LLMs to generate the translations with human annotated errors as the hint. The first instruction guarantees the basic translation ability of LLMs while the latter two regulate the LLMs to align with human feedbacks (Ouyang et al., 2022; Liu et al., 2023). While we only use the above instruction types in this paper, it is natural to extend PARROT to other hints (e.g., entity alignments), which we leave for future exploration.

We adopt the open-sourced LLaMA-7b (Touvron et al., 2023) and BLOOMZ-7b-mt (Scao et al., 2022) as our base models, and conduct instruction tuning on previous WMT validation data and Multidimensional Quality Metric (MQM) human evaluation data. The resulting PARROT models are evaluated on Flores subsets and WMT22 test sets. Our main findings are summarized as below:

- Translation instruction, as expected, can improve the translation performance of LLMs significantly, especially for directions from English to other languages.
- Contrastive instruction does not work as expected, which may result from the subtle difference between translations by the competitive WMT systems.
- Error-guided instruction can further improve the performance when asking PARROT to generate translations with no error, indicating the importance of learning from low-quality translations annotated by human.
- Parameter efficient finetuning with low rank adaptation (LoRA, Hu et al., 2022) can prevent LLMs from overfitting, which achieves better performance on dominant languages but slows down the learning from other languages.
- With the Alpaca multi-task dataset involved, PARROT can also preserve the capability of general tasks, such as question answering and code generation.

2 Instruction Pool

In this section, we introduce our instruction pool based on human written translations and evaluation data. Specifically, three distinct instruction types are included, namely, translation instruction, contrastive instruction, and error-guided instruction. The first instruction guarantees the basic translation ability of LLMs while the latter two regulate the LLMs to align with human feedbacks.

2.1 Translation Instruction

As traditional translation systems, we rely on bilingual sentence pairs to accomplish the basic translation ability of LLMs. We follow Stanford Alpaca (Taori et al., 2023) to transform bilingual sentence pairs into the instruction-following format, named **translation instruction**, for finetuning.

Table 1 presents an example of the translation instruction, which includes a preface fixed for all tasks, an “### Instruction:” to describe the translation task (e.g., stating the language pair), an “### Input:” with the source sentence, and a “### Response:” with the target sentence to be generated. To ensure the high quality of sentence pairs, we use human written translations rather than public training data that could be potentially noisy.

Table 1: Instruction types for finetuning PARROT models.

Type	Instruction
	Below is an instruction that describes a task, paired with an input that provides further context. Write a response that appropriately completes the request.\n\n
Translation	<p>### Instruction: Translate the following sentences from Chinese to English.\n\n</p> <p>### Input: 检查情况显示，市场销售的粮油、肉类、水果、蔬菜、蛋奶等生活必需品供应充足，商品价格基本稳定，未发现严重违法违规行为，市场秩序总体平稳。 \n\n</p> <p>### Response:The inspection results showed that there was an adequate supply of daily necessities, including grain, oil, meat, fruit, vegetable, milk, and eggs in the market and commodity prices basically remain stable, the administration found no serious offensive and noncompliant conducts, and the market order remains stable on the whole.</p>
Contrastive	<p>### Instruction: Translate the following sentences from Chinese to English.\n\n</p> <p>### Input: 检查情况显示，市场销售的粮油、肉类、水果、蔬菜、蛋奶等生活必需品供应充足，商品价格基本稳定，未发现严重违法违规行为，市场秩序总体平稳。 \n\n</p> <p>### Hint: We prefer to translate it to\n\n</p> <p>### Response:<p>The inspection results showed that there was an adequate supply of daily necessities, including grain, oil, meat, fruit, vegetable, milk, and eggs in the market and commodity prices basically remain stable, the administration found no serious offensive and noncompliant conducts, and the market order remains stable on the whole.</p> rather than <p>The results of the inspection indicate the sufficient supply of living necessities on marketing including cereals and oils, meat, fruits, vegetables, eggs and milk, and the basically stabilized commodity price. The inspection hasn't found serious violation of laws and regulations. The market order is stable on an overall basis.</p></p>
Error-Guided	<p>### Instruction: We are translating the following sentences from Chinese to English. \n\n</p> <p>### Input: 检查情况显示，市场销售的粮油、肉类、水果、蔬菜、蛋奶等生活必需品供应充足，商品价格基本稳定，未发现严重违法违规行为，市场秩序总体平稳。 \n\n</p> <p>### Hint: A translation with major accuracy/mistranslation errors could be\n\n</p> <p>### Response:The results of the inspection indicate the sufficient supply of living necessities <v>on marketing</v> including cereals and oils, meat, fruits, vegetables, eggs and milk, and the basically stabilized commodity price. The inspection hasn't found serious violation of laws and regulations. The market order is stable on an overall basis.</p> <p>### Hint: A translation with minor fluency/grammar errors could be\n\n</p> <p>### Response:The results of the <v>inspection</v> indicate the sufficient supply of living necessities on marketing including cereals and oils, meat, fruits, vegetables, eggs and milk, and the basically stabilized commodity price. The inspection hasn't found serious violation of laws and regulations. The market order is stable on an overall basis.</p>

2.2 Contrastive Instructions

Besides the basic translation ability, we also want LLMs to understand the relative quality difference between translations. In this way, we may improve the quality of translations by asking LLMs to output the preferred ones. To realize this goal, we need multiple different translations for each source sentence, which can be acquired by the systems submitted to WMT competitions. Meanwhile, the human evaluation results of these systems also provide scores to reflect the quality differences.

As shown in Table 1, we form the response by concatenating two translations (e.g., linked by

“rather than”), in which the first translation has a higher quality score. Meanwhile, we indicate that the first translation is preferred in the “### Hint:” field. Essentially, the second translation acts like a negative sample to this sentence pair, which explains the name **contrastive instruction**.

2.3 Error-Guided Instructions

The potential problem of contrastive instruction is that, it only tells the LLMs that the two translations have quality differences but not clarify which kind of translation errors lead to such differences. However, we want LLMs to learn the correspondence

between the errors and the translations. With such a deeper understanding on the translation errors, we may ask LLMs to produce translations with no error so as to improve the quality.

We propose **error-guided instruction**. As shown in Table 1, we use the translation with errors annotated by the “<v></v>” span to form the response. Similar to contrastive instruction, we adopt the “### Hint:” field to indicate the error types. This kind of fine-grained error annotations also come from the human evaluation data.

3 Experimental Setups

3.1 Training Data

Alpaca Data. This dataset is built by Stanford Alpaca (Taori et al., 2023)¹ project, which contains 52.0K instruction-following data of multi-tasks for tuning the LLaMA (Touvron et al., 2023)² models. The dataset is a list of dictionaries with each contains three fields, namely, “instruction” describes the task the model should perform, “input” describes optional context or input for the task, and “output” describes the answer to the instruction as generated by text-davinci-003. We call these data **general instructions**, which enable the LLaMA models to perform well on general tasks.

WMT Validation Data. We use human written validation data from previous WMT competitions rather than public training data to avoid introducing noises into instruction tuning. In this version, we use the newstest2017-2020 of Chinese \leftrightarrow English (i.e., Zh \leftrightarrow En) and German \leftrightarrow English (i.e., De \leftrightarrow En) tasks, which consist of 51.2K sentence pairs for all the four directions. These sentence pairs are formed into the translation instructions.

MQM Human Evaluation Data. Our human evaluation data comes from the Multidimensional Quality Metrics (MQM) datasets (Freitag et al., 2021)³, which annotate the different translation errors (e.g., major accuracy/mistranslation, minor fluency/grammar) of top WMT systems. Due to its higher reliability than Direct Assessment, MQM was introduced to WMT competitions starting from

WMT20 but only provided for a few language pairs. In this version, we use the MQM data for the WMT20 En \Rightarrow De and Zh \Rightarrow En submissions.

These data are formed into the **contrastive instructions** based on the quality scores and the **error-guided instructions** based on the error annotations, respectively. We use 26K instructions from both instruction types to form a 52.0K dataset.

Automatically Assessed Data. Although the Direct Assessment (DA) data of WMT systems provide scores for language directions that lack MQM data (i.e., De \Rightarrow En, En \Rightarrow Zh), we find the DA score to be very unreliable as they could be quite different for two similar translations. Instead, we opt for automatic evaluation metrics like COMET to score the translations of WMT systems. We also heuristically determine a rough error level for each translation based on the COMET score, namely, Major Error: [0, 85]; Minor Error: (85, 90]; No Error: (90, 100]. This decision comes in part from the observation that the top commercial translation systems achieve COMET scores of nearly 90 on the Flores subset in Table 3.

Note: To obtain a set of diverse instructions, we use the three instructions in Jiao et al. (2023), including the one in Table 1, as the seeds to ask GPT-4 (OpenAI, 2023) to paraphrase them. In total, we have 33 different instructions that are randomly combined with the training examples.

3.2 Evaluation

Test Data. We evaluate the translation performance of LLMs on two sources of test sets:

- **Flores Subset:** This dataset is a subset of Flores benchmark, in which 50 sentences are sampled for German, English, Romanian and Chinese, respectively, for evaluating the translation performance of ChatGPT (Jiao et al., 2023)⁴.
- **WMT22 Test Sets:** We also use the test sets from WMT22 competition (Kocmi et al., 2022), which are constructed based on more recent content from various domains, including news, social, e-commerce, and conversational domains. The numbers of samples for De \Rightarrow En, En \Rightarrow De, Zh \Rightarrow En and En \Rightarrow Zh tasks are 1984, 2037, 1875 and 2037, respectively.

¹https://github.com/tatsu-lab/stanford_alpaca

²<https://github.com/facebookresearch/llama>

³<https://github.com/google/wmt-mqm-human-evaluation>

⁴<https://github.com/wxjiao/Is-ChatGPT-A-Good-Translator>

Metrics. For automatic evaluation, we adopt BLEU (Papineni et al., 2002) implemented in SacreBLEU (Post, 2018)⁵, and COMET (Rei et al., 2020)⁶ from Unbabel/wmt22-comet-da, which are driven by n -gram similarity and cross-lingual pretrained models, respectively.

3.3 Model Training

We conduct our experiments on open-sourced LLMs with HuggingFace Transformers⁷. The hyper-parameters for finetuning are basically consistent with that used in Stanford Alpaca (Taori et al., 2023). Specifically, we adopt LLaMA-7b (Touvron et al., 2023) and BLOOMZ-7b-mt (Scao et al., 2022) as base models, and finetune them to the following variants:

- **Alpaca**, as a reimplementation of the Stanford Alpaca model fine-tuned only on the Alpaca multi-task dataset.
- **PARROT**, finetuned on both the Alpaca multi-task dataset and WMT validation data.
- **PARROT-HINT**, finetuned on the Alpaca multi-task dataset, WMT validation data, MQM human evaluation data as well as the automatically assessed data.
- **LLMs-LoRA**, the above LLMs finetuned by low-rank adaptation (LoRA), which contains only around 4.2M tunable parameters with the default hyper-parameters.

We finetune the Alpaca and PARROT models for 3 epochs on the corresponding data combination. For PARROT-HINT, we finetune it for 1.5 epochs to maintain the similar training steps as PARROT. The LLMs-LoRA are finetuned for the same epochs as their corresponding full models. We conduct finetuning on 8 Nvidia A100 GPUs and utilize DeepSpeed⁸ ZeRO stage 3 for the model parallel.

4 Results

4.1 Ablation Study

Before diving into more experiments, we investigate some factors that may affect the translation performance of LLMs. By default, we conduct the

Table 2: Ablation study of key factors on Flores En \Rightarrow De subset with Alpaca based on LLaMA-7b.

Prompt	Instruct.	Search	BLEU	COMET
no-input	TP1	sample	20.09	80.03
		beam 4	22.19	79.13
	TP3	sample	19.43	79.00
		beam 4	21.52	79.08
input	TP1	sample	21.00	79.51
		beam 4	23.32	80.56
	TP3	sample	19.33	78.68
		beam 4	20.64	80.07

ablation studies on the Flores En \Rightarrow De subset with the Alpaca model based on LLaMA-7b.

Prompt Format. In the Alpaca multi-task dataset, about 60% examples contain empty “### Input:”, which results in two different prompt formats during finetuning, i.e., prompt-input and prompt-no-input. During inference, they use prompt-no-input which combines the instruction and input to fill the “### Instruction:” field, introducing the inconsistency between finetuning and inference. Therefore, we study if such an operation makes any performance variation.

Instruction Variation. Recent studies (Jiao et al., 2023; Zhang et al., 2023) suggest that LLMs are sensitive to task instructions, which could vary the translation performance considerably. We conduct a brief study for this by comparing the TP1 and TP3 instructions in Jiao et al. (2023). TP1 is the one presented in Table 1 while TP3 is “Please provide the [TGT] translation for the following sentences.”, which was demonstrated a better choice when tested on ChatGPT⁹.

Search Algorithm. In machine translation, the beam search strategy (Sutskever et al., 2014; Freitag and Al-Onaizan, 2017; Vaswani et al., 2017) has been the standard search algorithm for inference, which finds a translation that approximately maximizes the conditional probability given by the translation model. However, beam search requires high computation costs which becomes infeasible with the LLMs, since they can easily induce out-of-memory (OOM) issues. Therefore, more efficient search algorithm such as sampling may have to be the choice. Therefore, we compare the sampling

⁵<https://github.com/mjpost/sacrebleu>

⁶<https://github.com/Unbabel/COMET>

⁷<https://github.com/huggingface/transformers>

⁸<https://github.com/microsoft/DeepSpeed>

⁹<https://chat.openai.com>

Table 3: Translation performance of LLMs on Flores subsets and WMT22 test sets.

System	De⇒En		En⇒De		Zh⇒En		En⇒Zh	
	BLEU	COMET	BLEU	COMET	BLEU	COMET	BLEU	COMET
Flores Subsets								
Google	45.04	88.79	41.16	88.61	31.66	87.71	43.58	88.42
DeepL	49.23	89.70	41.46	89.03	31.22	87.39	44.31	88.11
ChatGPT	43.71	89.10	38.87	88.14	24.73	85.81	38.27	86.99
GPT-4	46.00	89.31	45.73	89.28	28.50	87.42	42.50	88.40
<i>Base Model: LLaMA-7b</i>								
Vanilla	3.43	60.15	2.41	49.03	1.86	53.73	0.05	47.64
Alpaca	36.66	86.87	23.32	80.56	15.13	81.20	9.81	58.69
Alpaca-LoRA	40.77	87.70	24.64	84.07	16.42	81.59	14.51	70.52
PARROT	41.34	87.75	28.58	83.30	19.56	83.17	24.77	79.90
PARROT-HINT	41.07	87.97	30.83	84.38	19.22	83.96	25.84	80.15
+ Infer w/ Prefer.	38.10	87.60	23.07	83.97	18.69	83.10	22.54	80.12
+ Infer w/ No Err.	42.25	88.73	32.10	84.94	21.57	83.72	27.44	81.88
PARROT-HINT-LoRA	43.82	88.36	29.02	84.90	16.94	80.66	14.83	71.53
+ Infer w/ No Err.	42.01	88.08	29.89	85.40	17.43	81.38	19.89	76.78
WMT22 Test Sets								
WMT22 Winners	33.70	-/-	38.40	-/-	33.50	-/-	54.30	-/-
<i>Base Model: LLaMA-7b</i>								
Vanilla	2.90	52.81	1.63	45.36	1.25	50.34	0.38	46.38
Alpaca	27.82	82.33	20.17	78.13	14.24	74.00	10.44	62.10
Alpaca-LoRA	28.98	83.23	22.19	81.33	16.13	75.63	16.34	70.63
PARROT	26.61	82.57	24.03	80.43	18.10	75.38	27.08	78.45
PARROT-HINT	27.33	82.47	24.68	81.22	18.90	75.26	28.15	79.31
+ Infer w/ No Err.	27.38	82.47	26.14	81.67	20.23	75.90	30.33	80.34
PARROT-HINT-LoRA	28.85	82.88	24.04	81.47	18.27	74.77	19.93	73.70
+ Infer w/ No Err.	29.86	83.08	24.89	81.68	19.20	75.00	20.76	74.51
<i>Base Model: BLOOMZ-7b-mt</i>								
Vanilla	11.15	66.38	2.24	47.07	0.25	57.62	0.94	47.67
Alpaca	17.60	73.02	3.11	44.51	13.04	76.40	23.96	81.88
PARROT-HINT	23.15	77.62	20.01	72.73	21.46	78.57	32.40	83.69
+ Infer w/ No Err.	24.96	78.09	20.56	73.62	22.72	79.00	34.58	83.54

strategy (Taori et al., 2023) and the beam search strategy with a beam size of 4 for this factor.

Table 2 presents the results of these ablation studies. We have the following observations: (1) The prompt-input performs slightly better than prompt-no-input though the gap is marginal. (2) The TP1 instruction works better on Alpaca than TP3 which is different from that on ChatGPT. (3) Generally, beam search outperforms sampling significantly, especially in terms of BLEU score. Therefore, we use prompt-input + TP1 + beam search as the default setting for inference.

4.2 Main Results

Table 3 presents the translation performance of LLMs on the two benchmarks, i.e., Flores subsets and WMT22 test sets. For Flores subsets, we also include the results reported in Jiao et al. (2023) on ChatGPT and GPT-4. For models based on BLOOMZ-7b-mt, we only evaluate them on WMT22 test sets since the Flores benchmark has been used in the training process of BLOOMZ-7b-mt.

Instruction tuning exploits the potential of vanilla LLMs for machine translation. Obviously, the vanilla LLaMA-7b performs badly on the

Flores subsets. By inspecting the outputs, we find that the vanilla LLaMA-7b model tends to generate very long sentences (e.g., copy the instructions, continuing text expansion), which makes the generated text not faithful to the source sentences and also not grammatically correct. The reason could be the long context modeling during pretraining. Another reason is that we use the Alpaca inference format, which is basically a zero-shot setting that exhibits no guidance for translation.

Tuning LLaMA-7b on the Alpaca multi-task dataset (i.e., Alpaca) can ameliorate the above issue, resulting in complete generations with proper lengths. We find that Alpaca performs much better on translation, which may benefit from the 0.5% translation instructions in the Alpaca multi-task dataset. However, the best performance is mainly observed on high-resource directions like De \Rightarrow En, due to the dominant language of Alpaca dataset in English. Further introducing a small amount of translation instructions (i.e., PARROT) in the four language directions can significantly improve the performance, especially for En \Rightarrow Zh, in which Chinese was unseen in the pretraining of LLaMA models (Touvron et al., 2023). The findings of these LLaMA-based models are also consistent on WMT22 test sets.

Learning from low-quality translations annotated by human is also important. While presenting the high-quality bilingual pairs to LLMs is important, as discussed above, we argue that low-quality translations annotated by human also bring benefits. As shown in Table 3, with no hint for inference, PARROT-HINT outperforms PARROT slightly on translation directions from English to other languages (i.e., En \Rightarrow De, En \Rightarrow Zh). However, when asking PARROT-HINT to generate translations with no error, the performance can be significantly improved across translation directions and test sets. We speculate that PARROT-HINT does learn the relationship between errors and translations by error-guided instruction, such that it can avoid the translation errors as much as possible when the hint of no error is provided.

A bit unexpected is that when asking PARROT-HINT to generate preferred translations, the performance drops considerably. As stated in Section 2.3, contrastive instruction only indicates that two translations may have quality differences but not states why, which is difficult for LLMs to identify by themselves. Previous study by Min et al. (2022)

Table 4: Effects of error levels as hints during inference on Flores subsets.

Hint	En \Rightarrow De		Zh \Rightarrow En	
	BLEU	COMET	BLEU	COMET
None	30.83	84.38	19.22	83.96
No Err.	32.10	84.94	21.57	83.72
Minor Err.	28.84	83.60	20.67	82.14
Major Err.	28.57	82.93	19.33	80.55

also suggests that it is easier for LLMs to learn the instruction formats rather than the input-response patterns, which may explain the phenomenon here.

Our PARROT framework also proves effective on the LLMs based on BLOOMZ-7b-mt. One different behavior of them is that they perform much better on Zh \Rightarrow En and En \Rightarrow Zh directions than the LLMs based on LLaMA-7b, which mainly results from the better modeling of Chinese during the pretraining of BLOOMZ-7b-mt.

Parameter efficient finetuning may prevent LLMs from overfitting.

We also try low rank adaptation (LoRA, Hu et al., 2022) to fine-tune partial parameters of LLMs for efficiency. The hyper-parameters of LoRA come from alpaca-lora¹⁰, which results in only 4.2M tunable parameters of LLaMA-7b. Experimental results in Table 3 show that Alpaca-LoRA outperforms its full model counterpart with noticeably. We speculate that LoRA can prevent LLMs from overfitting the small Alpaca multi-task dataset, leading to a stronger generalization ability. However, applying LoRA to PARROT exhibits distinct behaviors for high-resource and low-resource translation directions. Specifically, PARROT-HINT-LoRA outperforms the corresponding full model PARROT-HINT on De \Rightarrow En but performs much worse on the other directions. It seems that the small amount of tunable parameters also hinder the learning of instructions from other translation directions. Obviously, the hyper-parameters of LoRA should also be properly adjusted to better learn from more instruction data.

4.3 Analysis

We conduct more analyses to understand the effects of our instruction types. By default, we use the models variants based on LLaMA-7b.

¹⁰<https://github.com/tloen/alpaca-lora>

Table 5: Examples from Flores Zh \Rightarrow En subset when translated with varied error levels.

COMET		Example
SRC	n/a	例如，在卢瓦尔河谷和莱茵河谷参观城堡，或者乘游轮去游览多瑙河沿岸好玩的城市，或者沿伊利运河乘船游玩。
REF	n/a	For example visiting castles in the Loire Valley, the Rhine valley or taking a cruise to interesting cites on the Danube or boating along the Erie Canal.
None	81.22	For example, visiting the castles in the Rhine Valley and the Lahn Valley , or taking a cruise along the Rhine River to explore the cities along the river , or taking a boat trip along the Illi River .
No Err.	81.49	For example, visiting the castles in the Rhine Valley and the Ruhr Valley , or taking a cruise to visit the cities along the Rhine River , or taking a boat ride along the Illi River .
Minor Err.	78.12	For example, visiting the castles in the Rhine Valley and the Ruhr Valley , or taking a cruise to visit the cities along the Rhine River , or taking a boat to play in the cities along the Elbe River .
Major Err.	65.39	For example, visiting the fortress in the valley of the River Volga and the River Levan , or taking a cruise to visit the cities along the River Volga , or taking a boat to play in the cities along the River Volga .

Table 6: Effects of preference as hint during inference on Flores subsets.

Hint	En \Rightarrow De		Zh \Rightarrow En	
	BLEU	COMET	BLEU	COMET
None	30.83	84.38	19.22	83.96
Prefer.	23.07	83.97	18.69	83.10
Unprefer.	29.19	83.76	19.68	82.35

Effectiveness of Error-Guided Instruction. To understand how error-guided instruction works, we investigate the behavior of PARROT-HINT when asking it to generate translations with varied error levels as hints. As shown in Table 4, the translation quality is getting worse from no error to minor error to major error, especially in terms of COMET score. **The translations generated with no hint are usually comparable with the minor error level.** It demonstrates that PARROT-HINT can place the erroneous translations into other locations of the probability space with the regulation of human annotations. As a result, PARROT-HINT is more likely to generate high-quality translation with “no error”.

For qualitative analysis, we show an example from Flores Zh \Rightarrow En subset in Table 5, in which we highlight all errors in each translation. Compared to no error level, minor and major error levels tend to produce more over-translations and mis-translations. **It is also important to point out that no error level does not guarantee that completely correct translations will be generated, especially for named entities,** which we attribute to the under-

explored translation abilities of current LLMs.

Failure of Contrastive Instruction. We try to understand why contrastive instruction does not work. By examining the responses of PARROT-HINT when asking it to generate preferred translations, we observe significant differences of lexical choices between the “preferred” and “unpreferred” (i.e., the second translation in the response) translations. **Surprisingly, as shown in Table 6, the “unpreferred” translations obtain much higher BLEU score though the situation is not for COMET score.** It indicates that PARROT-HINT attempted to identify the quality differences between the first and second translations in the contrastive instructions through lexical choices, which is a low-level pattern to reflect the translation quality. One potential reason is that the WMT systems are so competitive with each other that the quality differences between them are too subtle for the LLM to learn effectively. We will investigate more about the contrastive instruction in future work.

General Abilities. In our experiments, we include the Alpaca multi-task dataset for finetuning PARROT-HINT to preserve its ability on general tasks. We present two examples in Table 7, from question answering and code generation, respectively. As shown, the responses of both Alpaca and PARROT-HINT are correct, although the expressions may be different. For comprehensive comparison, it is better to perform a quantitative evaluation and we leave it for future work.

Table 7: Examples of general tasks.

System	Question Answering
	Tell me about alpacas.
Alpaca	Alpacas are a species of camelid native to South America. They are domesticated and bred for their fiber, which is used in the production of knitted and woven items such as clothing, blankets, and rugs. Alpacas are typically kept as livestock, and can live up to 20 years in captivity. They are typically brown, white, or grey in color, and can grow up to 12 inches tall at the shoulder.
PARROT-HINT	Alpacas are a species of domesticated South American camelids, bred primarily for their fiber. They are typically kept as pets, for their fleece, or for their meat. Alpacas are very social animals and live in herds, with a dominant male leader and a number of females and young. They are very intelligent and can be trained to respond to basic commands. Alpacas require a lot of space and good quality food in order to thrive.
System	Code Generation
	Write a Python program that prints the first 10 Fibonacci numbers.
Alpaca	<pre> numbers = [0, 1] for i in range(2, 10): numbers.append(numbers[i-2] + numbers[i-1]) print(numbers) </pre>
PARROT-HINT	<pre> def fibonacci(n): if n == 0: return 0 elif n == 1: return 1 else: return fibonacci(n-1)+fibonacci(n-2) print(fibonacci(10)) </pre>

5 Conclusion

Superior large language models (LLMs) like ChatGPT and GPT-4 are only accessible through restricted APIs, which creates barriers to new research and advancements in the field. In this paper, we propose the PARROT framework to enhance and regulate the translation abilities during chat based on open-sourced LLMs (i.e., LLaMA-7b) and human written translation and evaluation data. Specifically, PARROT reformulates translation data into the instruction-following style, and introduces a “Hint” field for incorporating extra requirements to regulate the translation process. Accordingly, we propose three instruction types for finetuning PARROT models, including translation instruction, contrastive instruction, and error-guided instruction. We can finetune either the full model of LLMs or partial parameters via LoRA. Experiments on Flores subsets and WMT22 test sets suggest that translation instruction improves the translation performance of vanilla LLMs significantly while error-guided instruction can lead to a further improvement, which demonstrates the importance of learning from low-quality translations annotated by human. Meanwhile, the PARROT models can also preserve some abilities on general tasks with the

Alpaca multi-task dataset involved in finetuning.

In the future, various aspects can be explored to improve PARROT, for example: (1) taking the advantages of other hints like entity alignments or domain styles; (2) extending the coverage of translation directions; and (3) exploring parameter-efficient finetuning techniques for larger language models, especially on how the hyper-parameters affect the learning pace.

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