Mitigating the Language Mismatch and Repetition Issues in LLM-based Machine Translation via Model Editing

Anonymous ACL submission

Abstract

Large Language Models have recently revolutionized the NLP field, while they still fall short in some specific down-stream tasks. In the work, we focus on utilizing LLMs to perform machine translation, where we observe that two patterns of errors frequently occur and drastically affect the translation quality: language mismatch and repetition. The work sets out to explore the potential for mitigating these two issues by leveraging model editing methods, e.g., by locating FFN neurons or something that are responsible for the errors and deactivating them in the inference time. We find that directly applying such methods either limited effect on the targeted errors or has significant negative side-effect on the general translation quality, indicating that the located components may also be crucial for ensuring machine translation with LLMs on the rails. To this end, we propose to refine the located components by fetching the intersection of the locating results under different language settings, filtering out the aforementioned information that is irrelevant to targeted errors. The experiment results empirically demonstrate that our methods can effectively reduce the language mismatch and repetition ratios and meanwhile enhance or keep the general translation quality in most cases.

1 Introduction

Pre-trained Large Language Models (LLMs) are natural machine translators with in-context learning(Brown et al., 2020; Touvron et al., 2023; Vilar et al., 2023; Bawden and Yvon, 2023; Zhang et al., 2023a), while they still fall behind specialized Machine Translation (MT) systems like NLLB(Koishekenov et al., 2023). Previous studies utilise In-Context Learning (Agrawal et al., 2023) (ICL), instruction tuning(Xu et al., 2023; Alves et al., 2023) and post-editing methods(Jiao et al., 2023; Ki and Carpuat, 2024; Raunak et al., 2023)

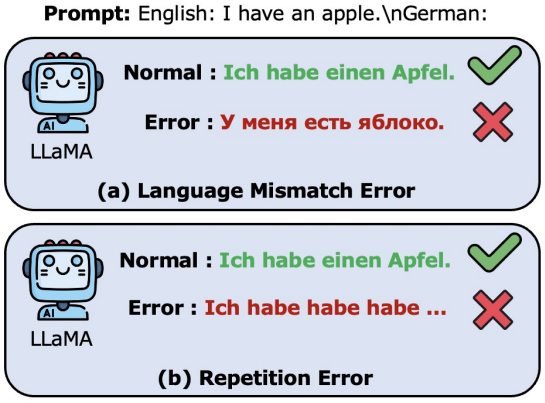


Figure 1: The illustration of the language mismatch error (a) and the repetition error (b).

to improve the translation quality. *Are there any issues that were ignored in previous studies hindering the LLM-based machine translation from further development?* In this work, we identify two issues in the LLM-based machine translation: *Language Mismatch* and *Repetition* (as shown in Figure 1). We check the occurrence of these errors and find that: (1) they are common errors in the whole translation set (e.g., in the en→de setting, language mismatch occurs in over 40% cases with zero-shot prompting); (2) they are severe errors for machine translation systems (e.g., repetition errors usually lead to a over 50% decrease on the BLEU score).

Nonetheless, the inherent reason for these errors still remains unclear, let alone patching them. In recent research works on model editing (Dai et al., 2022; Meng et al., 2022; Todd et al., 2023), they typically leverage analyzing tools like causal mediation analysis (Pearl, 2014; Vig et al., 2020), integrated gradient attribution (Sundararajan et al., 2017) to locate important component units (e.g., FFN neurons, attention heads and stuff) that are highly responsible for specific behavior patterns of LLMs, and then precisely control these behaviors by manipulating the located components (e.g.,

amplifying and suppressing the activation values of neurons). Inspired by these works, we ask a research question: *Can we leverage model editing methods to mitigate aforementioned language mismatch and repetition issues?* We set out to adapt two widely-used model editing technique, Function Vectors (Todd et al., 2023) (FV) and Knowledge Neurons (Dai et al., 2022) (KN), to MT scenarios in an aim to locate error-relevant component units inside LLMs. However, our empirical results show that directly adapting FV and KN either has limited effect on the targeted errors or has significant side-effect on the general translation quality, which indicates that the located component units may be not only responsible for targeted error patterns but also crucial for ensuring machine translation with LLMs on the rails and hence manipulate them could result in affecting the general translation behavior.

We then aim to filter out the error-irrelevant components from the located results. A natural hypothesis is that *the location for the important error-relevant modules is supposed to be independent to translation language settings.* Comparing the locating results under the different translation language settings (de→en, en→de, zh→en and en→zh), we do observe that a proportion of located component units are shared across different language settings. Grounded on this observation, we propose to refine the located components by fetching the intersection of the locating results under different language settings. The empirical results demonstrate that the modified methods can effectively reduce the language mismatch and repetition ratios and meanwhile keep or enhance the general translation quality in most cases.

Our main contributions are three-fold: (1) We identify two patterns of errors in LLM-based MT that frequently occur and badly affect the translation quality: language mismatch and repetition. (2) We investigate the potential for leveraging model editing methods (FV and KN) to reduce these errors. We find that directly adapting the editing methods either has limited effect on the targeted errors or has significant side-effect on the general translation quality. (3) We propose to refine the located modules by fetching the intersection of the locating results under different language settings. We show that with the refined locating results we could arouse the potential for editing methods to handle the language mismatch and repetition errors and meanwhile enhance or keep the general translation quality in most cases. The performance of our methods could sometimes be comparable with traditional methods that adapt LLMs to MT tasks (e.g., 5-Shot ICL, LoRA and Full-FineTuning) without additional requirements like long-context prompting and fine-tuning.

2 Related Work

Large Language Models for Machine Translation One surprising ability of LLMs is that they are natural machine translators with Zero-Shot or One-Shot prompt(Brown et al., 2020; Touvron et al., 2023; Vilar et al., 2023; Bawden and Yvon, 2023; Robinson et al., 2023; Zhang et al., 2023a). However, there is still a gap(Xu et al., 2023) between pre-trained LLM and large-scale NMT systems like NLLB(Koishekenov et al., 2023) on the machine translation task. To bridge this gap, previous studies utilise in-context learning(Moslem et al., 2023; Agrawal et al., 2023; Bawden and Yvon, 2023; Vilar et al., 2023), model tuning(Xu et al., 2023; Alves et al., 2023; Zhang et al., 2023b), and interaction with annotation methods(Jiao et al., 2023; Ki and Carpuat, 2024) to improve the translation quality. Even though LLM has achieved massive success in machine translation(Kocmi et al., 2023a), some of the issues from LLM itself may challenge machine translation, such as Hallucination(Bang et al., 2023). Meanwhile, these problems from LLM are challenging to detect only with MT metrics. Alves et al. (2023) find few-shot tuning can improve the translation quality based on MT metrics(Papineni et al., 2002; Rei et al., 2022) but detect the machine translation hallucination with a case-based hallucination design.

Locating Based Model Editing Precisely locating a small set of important modules (e.g., neurons (Dai et al., 2022), hidden states (Todd et al., 2023), MHSA (Li et al., 2024) and MLP (Meng et al., 2022) outputs) and editing their values to steer large-scale models toward assumed behaviours (e.g., updating factual associations (Meng et al., 2022; Hase et al., 2023), detoxifying (Wang et al., 2024), decreasing hallucination (Li et al., 2023), switching languages (Tang et al., 2024) and patching reasoning errors (Li et al., 2024)) is a recently emerging paradigm. Nonetheless, such techniques are still largely under-explored in context of MT. In this work, we investigate the potential for adapting two representative locating based editing approaches (specifically, function vectors (Todd et al., 2023) and knowledge neurons (Dai et al., 2022))

to the MT scenario to mitigate its two fundamental but crucial issues: language mismatch and repetition (Zhang et al., 2021).

3 Preliminary

In this section, we detail the data preparation process, including the data source, prompt template, and dataset construction. Additionally, we provide information about the model and the evaluation metrics used to support the ensuing experiments.

Data Source We choose three high-resource languages: *English, Chinese, German* which show good performance on MT tasks(Robinson et al., 2023). For the detailed language setting, we include two language pairs: English-Chinese and English-German, and four translation directions: en→de, de→en, en→zh and zh→en (where en, de, zh represent English, German and Chinese, respectively). In the data choice, we use the human-made dataset from general MT tasks of WMT21, WMT22 and WMT23 [1] to ensure both high data quality and flexible data domain. These data make the machine translation approach a real-life usage to help us understand the current state of machine translation tasks using LLMs.

Prompt Template For machine translation tasks, a widely-adopted (Zhang et al., 2023a; Bawden and Yvon, 2023; Vilar et al., 2023) K-Shot In-Context Learning (ICL) prompt template (taking the language setting of en→zh for an example) is:

$$\begin{aligned}&\text{English}: src_1 \backslash n \text{Chinese}: tgt_1 \backslash n\\&\ldots\\&\text{English}: src_K \backslash n \text{Chinese}: tgt_K \backslash n\\&\text{English}: src_q \backslash n \text{Chinese}:\end{aligned}$$

Where (src_i, tgt_i) refers to the i-th in-context translation exemplar (src_i refers to a sentence of source language and tgt_i refers to the corresponding sentence of target language.). src_q refers to the real sentecne of source language that needs to be translated. We call this prompt template *Lang Prompt* and regard it as the default prompt template for the follow-up experiments in this paper.

Dataset Construction In the data construction part, we construct the $\mathcal{D}_{exps}$ (data from WMT21) to provide the ICL exemplars used in the K-Shot prompt for machine translation tasks. We use the WMT22 data as the $\mathcal{D}_{train}$ to fine-tune a model or locate the critical parts in an LLM for model editing methods. For the testing and validation, we construct the $\mathcal{D}_{test}$ (data from WMT23) for various modifications (e.g. fine-tuning(Devlin et al., 2019) or model editing methods(Todd et al., 2023; Dai et al., 2022)). (Please refer to Appendix A for detailed dataset information)

Model To support the in-depth exploration and analysis of how the two kinds of errors happen. We use LLaMA2-7B as our backbone language model to implement the machine translation task and further adaptation(Touvron et al., 2023).

Evaluation Metrics For the machine translation metrics, we consider the overlapping-based metrics BLEU(Papineni et al., 2002) and neural-based metrics COMET(Rei et al., 2022) to evaluate the translation quality (For a detailed toolkit and detection process, please refer to Appendix B).

4 Language Mismatch and Repetition Error in LLM-MT

In our initial experiments, we observe that LLM-based machine translation struggles with the following two types of common errors. One is **Language Mismatch**, referring to the language of the translation result is not the target language. For example, In the en→zh machine translation, the target language is Chinese while the language of generated sentence is still English. Another is **Repetition**, referring to a substring is generated repeatedly until the end of the generation. To evaluate these errors, we additionally introduce two metrics: **L**anguage **M**ismatch **R**atio (LMR) (the percentage of cases occurring the language mismatch error) and **R**epetition **R**atio (RR) (the percentage of cases occurring the repetition error).

Language mismatch and repetition error are common and crucial In this paragraph, we aim to find the ratio of language mismatch and repetition error in Zero-Shot and One-Shot. For detailed language settings, we consider en→de, de→en, en→zh, and zh→en. We use the $\mathcal{D}_{test}$ and $\mathcal{D}_{exps}$ as the test set and prompt exam source, respectively. We choose LER and RR to represent the ratio of language mismatch and repetition in a setting (e.g. en→de (Zero-Shot)). For translation quality evaluation, we choose the BLEU (Papineni et al., 2002) as the metrics. We observe that language mismatch is frequent in Zero-Shot and seldom in One-Shot.

[1] https://github.com/wmt-conference/wmtX-news-systems. X∈ {21, 22, 23}

Repetition error cases in One-Shot are without language mismatch but combined with language mismatch in Zero-Shot. Based on our observation, we do experiments and analysis in Zero-Shot for the language mismatch and in One-Shot for the repetition error.

To explore the relation between the above errors and translation quality, we split the translation results into four sets to evaluate the BLEU performance after error detection. The four sets include two error sets: *language mismatch set* and *repetition error set*, one *regular set* (where instance without both errors), and one *Origin set* that includes all cases. The results of Table 1 illustrate: (1) the gap between the regular set and the original set shows both language mismatch and repetition error hurt the translation quality; (2) Language mismatch is the main reason for the low performance in Zero-Shot; (3) Even though we observe a low repetition ratio in One-Shot, the gap between repetition set and regular set shows that repetition is a severe error in the original set; (4) The performance gap between regular and error cases indicates a direct way to improve the translation quality by eliminating these errors.

Setting	**L**(↓)	**OB**(↑)	**LB**(↑)	**RB**(↑)
zh→en **(Z)**	0.0486	17.13	8.77	17.60
en→zh **(Z)**	0.3269	16.34	3.13	25.29
en→de **(Z)**	0.4524	12.61	1.65	21.86
de→en **(Z)**	0.0219	35.34	23.23	35.66
Setting	**R**(↓)	**OB**(↑)	**RRB**(↑)	**RB**(↑)
zh→en **(O)**	0.0035	18.87	2.13	19.06
en→zh **(O)**	0.0146	27.78	2.08	29.47
en→de **(O)**	0.0141	24.97	12.64	25.86
de→en **(O)**	0.0018	36.54	6.10	36.71

Table 1: The correlation between error ratio and BLEU. **(Z)** represents the Zero-Shot prompting, and **(O)** represents the One-Shot prompting. **L**: language mismatch ratio; **R**: repetition ratio; **OB**: The BLEU on the original set; **LB**: The BLEU on the language mismatch set; **RRB**: The BLEU on the repetition error set; **RB**: The BLEU on the regular set.

5 Can we mitigate language mismatch and repetition via model editing?

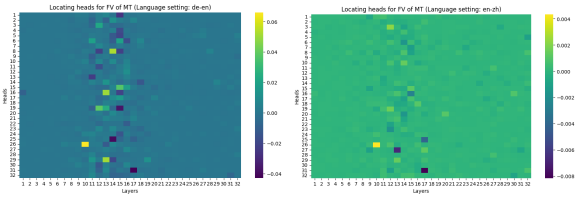
In this section, We aim to investigate the potential for leveraging model editing methods (Dai et al., 2022; Meng et al., 2022; Todd et al., 2023) to precisely mitigate the aforementioned two severe issues in MT: language mismatch and repetition. We mainly focus on two widely-used model editing methods: **F**unction **V**ectors (**FV**) (Todd et al., 2023) and **K**nowledge **N**eurons (**KN**) (Dai et al., 2022), for both of them are representative (i.e., Causal Mediation Analysis (Meng et al., 2022; Pearl, 2014) for FV and Integrated Gradient Attribution (Qi et al., 2019; Lundstrom et al., 2022) for KN) and influential (Bai et al., 2024; Hojel et al., 2024; Niu et al., 2024; Chen et al., 2024). In the following paragraphs, we adapt the idea of FV (corresponding to **Machine translation vectors**) and KN (corresponding to **Machine translation neurons** and **Repetition neurons**) to MT scenarios, in an aim to both enhance the LLMs' understanding to MT (for both language mismatch and repetition errors) and their specific ability to handle repetition errors.

5.1 Machine Translation Vectors

In the original FV paper, the authors argue that the key information of a task (e.g., task $\mathcal{T}$, demonstrated with few-shot **I**n-**C**ontext **L**earning (ICL) exemplars in the prompt) is compactly represented and transported in a small set of attention heads in LLMs. The original definition for FV (of task $\mathcal{T}$) is the summation of these located head vectors. FV can be directly added into the "residual stream" (Elhage et al., 2021) of forwarding computation of Transformer-based (Vaswani et al., 2017) LLMs to help them perform ideal behaviour of task $\mathcal{T}$. Therefore, a natural question is: ***Can we use FV to enhance LLMs' understanding to MT and mitigate aforementioned language mismatch and repetition issues?*** We use Ten-Shot ICL prompts $\mathcal{P}$ (the template of machine translation prompts is the *Lang Prompt* (Zhang et al., 2023a) in Section 3.) to locate important attention heads, where the data are sampled from $\mathcal{D}_{train}$. For brevity, we denote the normal Ten-Shot ICL input (omitting language signs, i.e., "English", "Chinese" and "German") as: $inp = [(src_1, tgt_1), (src_2, tgt_2), ..., (src_{10}, tgt_{10}), src_q] \in \mathcal{P}$, where src and tgt refer to sentences of source and target languages respectively; index $1 \sim 10$ refers to ten ICL exemplars and q refers to "query" (the real source sentence that requires to be translated.). On its basis, we construct the *shuffled* version of the original ICL input: $\widetilde{inp} = [(src_1, \widetilde{tgt_1}), (src_2, \widetilde{tgt_2}), ..., (src_{10}, \widetilde{tgt_{10}}), src_q]$, where for each ICL exemplar $(src_k, \widetilde{tgt_k})$, $k \in [1..10]$, the target sentence $\widetilde{tgt_k} \neq tgt_k$.

Extracting machine translation vectors First, we locate attention heads that are important to the MT with a *Causal Mediation* procedure: (1) Send both inp and $\widetilde{inp}$ to the same LLMs (denoting the model as θ), (2) Fetch both probabilities of predicting the ground-truth target sentence tgt_q from models with the above two inputs: $p_\theta(tgt_q|inp)$ and $p_\theta(tgt_q|\widetilde{inp})$, (3) Adopt intervention: replacing *a single attention head output* (e.g., for the i-th head in the j-th layer, the denotation is $\widetilde{h}^i_j$.) in the shuffled run with $\widetilde{inp}$ with the attention head output at the same place (h^i_j) in the clear run with inp, (4) Calculate the **C**ausal **I**ndirect **E**ffect (CIE($\widetilde{h}^i_j \rightarrow h^i_j|inp$)) of the intervention: $p_\theta(tgt_q|\widetilde{inp}, \widetilde{h}^i_j \rightarrow h^i_j) - p_\theta(tgt_q|\widetilde{inp})$ and (5) Calculate the **A**verage **I**ndirect **E**ffect for head h^i_j: $\text{AIE}(h^i_j) = \mathop{\mathbb{E}}_{inp\in\mathcal{P}}[\text{CIE}(\widetilde{h}^i_j \rightarrow h^i_j|inp)]$.

The AIE values for all heads in LLaMA2-7B under the language settings[2] of "de→en" and "en→zh" are depicted in Figure2. We observe that



(a) de→en (b) en→zh

Figure 2: Heatmaps of AIE values for attention heads in LLaMA2-7B for de→en setting (a) and en→zh setting (b). x-axis and y-axis refer to the layer and head. Brighter color refers to the head with larger AIE value.

for machine translation there are sparsely a few heads of which the corresponding AIE values strikingly stand out among 1024 heads. We select top-32 heads (according to their AIE values, denoted as $\mathcal{H}$) to extract FV in the follow-up experiments.

Let $h^i_j(inp)$ denote the output of attention head h^i_j given the input prompt inp. Following Todd et al. (2023), we extract the machine translation vector with a specific language setting (e.g., zh→en) $\mathcal{V}_{\text{zh}\rightarrow\text{en}}$ with the following formula:

$$\mathcal{V}_{\text{zh}\rightarrow\text{en}} = \mathop{\mathbb{E}}_{inp\in\mathcal{P}_{\text{zh}\rightarrow\text{en}}}[\sum_{h^i_j\in\mathcal{H}} h^i_j(inp)] \quad (1)$$

Editing LLMs via machine translation vectors We directly add the extracted the machine translation vector to the "residual stream" (being aligned with the original paper, at 11-th layer for LLaMA2-7B) in the forwarding process. The performance of LLaMA2-7B (e.g., under the language setting of zh→en.) after adopting machine translation vectors are posted in Table 2.

[2]Due to the page limit, We post experiment results only under part of the language settings results in the main text. For the rest language settings, we post them in Appendix C, Similarly hereinafter.

Zero-Shot	**L**(↓)	**B**(↑)	**C**(↑)
LLaMA2-7B	0.0486	17.1288	0.722
+MT vectors	−72.84%	−37.35%	−1.84%
+MT neurons	−18.72%	−4.28%	−0.15%
One-Shot	**R**(↓)	**B**(↑)	**C**(↑)
LLaMA2-7B	0.0035	18.8714	0.7376
+MT vectors	482.86%	−23.07%	−1.68%
+MT neurons	0.0%	−0.35%	−0.03%
+RP neurons	−8.57%	0.07%	0.0%

Table 2: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language setting of zh→en). ***Zero-Shot*** and ***One-Shot*** refer to that using zero-shot prompt (for language mismatch errors) and one-shot prompt (for repetition errors) for MT. For evaluation metrics, **L**: Language mismatch ratio; **R**: Repetition ratio; **B**: BLEU and **C**: COMET22DA, where **B** and **C** mainly evaluate the general translation quality. For plain LLaMA2-7B, the results are absolute values; for LLaMA2-7B with editing methods, the results are relative **improvement percentages**.

We observe that leveraging machine translation vectors (*+MT vectors*) can (1) reduce the language mismatch errors to a large extent (−72.84%) while simultaneously (2) introduce more repetition errors (+482.86%) and (3) do harm to the general translation quality: −37.35% (Zero-Shot) and −23.07% (One-Shot) for BLEU.

5.2 Machine Translation Neurons and Repetition Neurons

The original KN technique is constructed on the basis of Geva et al. (2021)'s observation that the Feed-Forward Networks (FFNs) in the Transformer (Vaswani et al., 2017) can be viewed as key-value memories, which can store the encodings of a set of patterns (e.g., sentence end with specific words, specific topics and factual knowledge.). Given a specific pattern, KN can be used to locate a small set of neurons in FFNs that are the attribution of this pattern and manipulate the expression of this pattern by amplifying, suppressing or erasing the activation values of the located neurons. We ask a natural question: ***Can we use KN to locate and manipulate skilled neurons that are responsible for MT or the repetition error pattern?*** In the MT scenarios, We denote the input prompt inp (also

omitting language sign) as $[src_q]$ (Zero-Shot) or $[(src_0, tgt_0), src_q]$ (One-Shot) and the corresponding output as tgt_q, where the (src_0, tgt_0) is the ICL exemplar (sampled from $\mathcal{D}_{exps}$) and (src_q, tgt_q) is the "query", the real case used for locating neurons (sampled from $\mathcal{D}_{train}$) or testing edited models (sampled from $\mathcal{D}_{test}$).

Locating Important Neurons for MT We randomly sample a token t in each tgt_q and use t to split tgt_q into two parts: $tgt_q = (\overleftarrow{tgt_q}, \overrightarrow{tgt_q})$ ($t \in \overrightarrow{tgt_q}$). To fully model the MT and meanwhile restrict the computation, we focus on the probability of $p(t|inp^+)$, where t refers to the first token of $\overrightarrow{tgt_q}$ and inp^+ refers to the concatenation of inp and $\overleftarrow{tgt_q}$. Focusing on a single neuron $w_i^{(l)}$ (i-th intermediate neuron in the j-th FFN), we denote its activation value as $\overline{w_i}^{(l)}$. Then we can introduce this variable into $p(t|inp^+)$ as $p(t|inp^+, w_i^{(l)} = \overline{w_i}^{(l)}) \triangleq f(\overline{w_i}^{(l)})$ (fixing t and inp^+, the probability can be viewed as an objective function whose only variable is the value of neuron $w_i^{(l)}$). We calculate the attribution score of neuron $w_i^{(l)}$ by Integrated Gradient (Sundararajan et al., 2017):

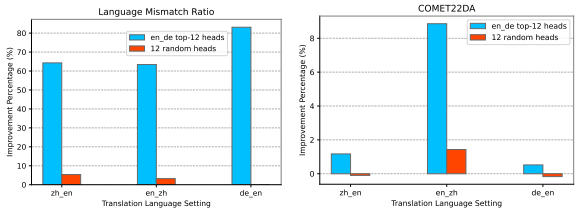
$$\text{Attr}(w_i^{(l)}|f) = \overline{w_i}^{(l)} \int_{\alpha=0}^{1} \frac{\partial f(\overline{w_i}^{(l)})}{\partial w_i^{(l)}} d\alpha. \quad (2)$$

We calculate the mean value of the attribution scores for each neuron with 2,000 examples in $\mathcal{D}_{train}$ and select top-5 neurons as Machine Translation neurons (*MT neurons*).

Locating Important Neurons for Repetition We first collect all of examples that occur the repetition error. For a specific input prompt inp, the completion of LLMs y can be divided into the following several parts: $y = [y_{norm}, y_{repe}, y_{repe}, y_{rest}]$, where y_{norm} refers to the normal generation part (except for the first-time generation of y_{repe}), y_{repe} refers to the minimal repetition unit (the first y_{repe} here is supposed to be treated as normal generation) and y_{rest} (the follow-up generation after the second-time generation of y_{repe}). To concentrate on the repetition error, we construct a new input prompt $inp_{repe} = [inp, y_{norm}, y_{repe}]$ and focus on the probability of $p(y_{repe}|inp_{repe})$. Similar to the *MT neurons* part, we define neuron $w_i^{(l)}$, its value $\overline{w_i}^{(l)}$, its objective function $p(y_{repe}|inp_{repe}, w_i^{(l)} = \overline{w_i}^{(l)}) \triangleq f_{repe}(\overline{w_i}^{(l)})$ and its attribution score $\text{Attr}(w_i^{(l)}|f_{repe})$ (repetition attribution score). A natural concern here is that ***the objective function*** $f_{repe}(\overline{w_i}^{(l)})$ ***might model the pattern of generating*** y_{repe} ***rather than the repetition error pattern***. To exclude this concern, we additionally set a comparison objective function $f_{compare} = p(y_{repe}|[inp, y_{norm}], w_i^{(l)} = \overline{w_i}^{(l)})$ to model the first-time generation (normal generation) of y_{repe}. With $f_{compare}$, we can also get the attribution score $\text{Attr}(w_i^{(l)}|f_{compare})$ (comparison attribution score) of neuron $w_i^{(l)}$. We calculate the mean values of repetition and comparison attribution scores separately for each neuron $w_i^{(l)}$ with all of the cases in $\mathcal{D}_{train}$ that occur the repetition error. We separately select top-300 neurons according to mean repetition and comparison attribution score, denoting the fetched sets as $\mathcal{N}_{repe}$ and $\mathcal{N}_{compare}$. We select 5 neurons with the largest repetition attribution scores from $\mathcal{N}_{repe} \backslash \mathcal{N}_{compare}$ as the Repetition Neurons (*RP neurons*).

Editing LLMs via *MT* neurons and *RP* neurons For *MT* neurons, we edit LLMs by *amplifying* the activation values of these neurons (set the new values to be twice the original ones). For *RP* neurons, we edit LLMs by *erasing* the activation values of these neurons (set the new values to be zero). The performance of LLaMA2-7B (e.g., under the language setting of zh→en.) after adopting *MT* neurons and *RP* neurons are posted in Table 2. We observe that (1) adopting *MT* neurons can indeed help reduce language mismatch ratio to some extent(-18.72%) while also bring small negative side-effect to the translation quality (-4.28% for the BLEU score), (2) adopting *MT* neurons nearly have no effect on the repetition ratio and (3) adopting *RP* neurons can reduce the repetition ratio slightly (-8.57%) without affecting the metrics (BLEU and COMET22DA) of evaluating general translation quality.

Hence a short response to the question of this section is that ***Directly leveraging model editing methods either has limited effect on errors (MT neurons and RP neurons) or significant negative side-effect on general translation quality (MT vectors)***. Nonetheless, we do observe the potential for mitigating the aforementioned errors with editing methods.



(a) Language Mismatch Ratio (b) COMET22DA

Figure 3: Performance ((a) for the decrease percentage of LMR; (b) for the improvement percentage of COMET22DA) of intervention (blue bars) with language settings of **zh**→**en**, **en**→**zh** and **de**→**en** on the heads located with the language setting of **en**→**de**. The red bars (comparison group) refer to the results for intervention on random heads of the same number.

Zero-Shot	**L**(↓)	**B**(↑)	**C**(↑)
LLaMA2-7B	0.0486	17.1288	0.722
+MTV	**−92.46%**	−0.81%	2.65%
+MTV-I	−80.15%	53.5%	15.51%
+MTV-I-D	−86.12%	**76.82%**	**16.02%**
One-Shot	**R**(↓)	**B**(↑)	**C**(↑)
LLaMA2-7B	0.0035	18.8714	0.7376
+RPN	−8.57%	0.07%	**0.0%**
+RPN-I	**−25.71%**	**0.51%**	−0.04%

Table 3: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language settings of zh→en for ***Zero-Shot*** and zh→en for ***One-Shot***). Other notations and abbreviations are following Table 2.

6 Modifications to FV and KN in MT scenarios

In section, we mainly discuss our modifications (Section 6.1) to FV and KN methods (Section 5) to release their potential for better mitigating the language mismatch errors, repetition errors and even improving the general translation quality. Besides, we present systematical evaluation results for the modified editing methods and baselines in Section 6.2.

6.1 Modifications

Previous empirical results (Section 5) show that *MT vectors* are more effective to reduce language mismatch errors in comparison with *MT neurons* while the *RP neurons* are more promising for handling repetition errors, suggesting that the inherent mechanisms for the recognition of target language and generating strings repeatedly locate in MHSA heads and FFN intermediate neurons, respectively. To this end, in the follow-up experiments, we concentrate on modifying *MT vectors* to handle language mismatch errors and *RP neurons* to handle repetition errors. Our first modification is based on a natural hypothesis: ***The location for the important modules inside LLMs that are responsible for target language recognition and repetition errors is supposed to be independent to language settings.*** The hypothesis can also be verified to some extent by the important head locating experiments depicted in Figure 4, where results for different language settings (**zh**→**en**, **en**→**zh**, **en**→**de** and **de**→**en**) share a large proportion of top heads. Moreover, we locate top-12 important attention heads in LLaMA2-7B under the language setting of en→de and apply *MT vectors* to LLaMA2-7B with these located heads under the language settings of **zh**→**en**, **en**→**zh** and **de**→**en**. The results of Zero-Shot translation are depicted in Figure 3 (experimental group, blue bars). We additionally randomly select 12 heads to apply *MT vectors* and the results (comparison group) are shown with red bars. We observe that for both the language mismatch ratio and COMET22DA, the performance of experimental group largely exceeds the performance of comparison group under all three other language settings, indicating that the attention heads located under a single language setting can transfer to other language settings. Given these evidences, we propose our first modification to both *MT vectors* and *RP neurons*: ***We firstly locate attention heads or FFN neurons separately for each language setting and then get the final located results by intersecting the located results for all of language settings.*** We denote the MT vectors fetched by intersected attention heads as ***MT Vectors-Intersection*** (*MTV-I*) and intersected RP neurons as ***RePetition Neurons-Intersection*** (*RPN-I*). We post the results for leveraging *MTV-I* and *RPN-I* under the language settings of en→de and zh→en in Table 3. We observe that: (1) for *MTV-I*, the decrease percentage of language mismatch error ratio (−80.15%) is slightly lower than *MTV* (−92.46%) while improvement percentage of the BLEU score (53.5%) and COMET22DA score (15.51%) exceed *MTV* (−0.81% and 2.65%) by a large margin and (2) for *RPN-I*, the decrease percentage of repetition error ratio (−25.71%) is much higher than RPN (−8.57%), suggesting that intersection of different language settings can filter attention heads and FFN neurons that are irrelevant to language mismatch errors and repetition errors out. On the basis of *MTV-I*, we propose another slight modification: ***Firstly calculate the MTV-I,***

	de→en		en→de		zh→en		en→zh	
Zero-Shot	**L**(↓)	**B**(↑)	**L**(↓)	**B**(↑)	**L**(↓)	**B**(↑)	**L**(↓)	**B**(↑)
LLaMA2-7B	0.0219	35.3448	0.4524	12.6084	0.0486	17.1288	0.3269	16.3441
+5-Shot ICL	−74.89%	4.93%	−92.06%	101.27%	−50.0%	12.46%	−82.59%	76.9%
+LoRA	−83.56%	0.68%	−95.25%	115.24%	−79.22%	6.62%	−77.58%	82.62%
+Full-FT	−8.68%	2.25%	−62.69%	55.41%	−33.33%	3.15%	−66.23%	62.64%
+*MTV-I-D*	−33.33%	−0.53%	−86.12%	76.82%	−54.12%	−14.08%	−69.9%	24.64%
One-Shot	**R**(↓)	**B**(↑)	**R**(↓)	**B**(↑)	**R**(↓)	**B**(↑)	**R**(↓)	**B**(↑)
LLaMA2-7B	0.0018	36.5445	0.0141	24.9685	0.0035	18.8714	0.0146	27.7798
+5-Shot ICL	0.0%	1.49%	14.89%	1.63%	−14.29%	2.07%	−17.12%	4.08%
+LoRA	−77.78%	−9.47%	−74.47%	−2.39%	5.71%	0.07%	−10.27%	0.37%
+Full-FT	22.22%	1.26%	−25.53%	4.9%	−22.86%	2.5%	22.6%	4.47%
+*RPN-I*	−38.89%	0.74%	−27.66%	0.35%	−25.71%	0.51%	−19.18%	−0.23%

Table 4: Overall Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ under all language settings. Other notations and abbreviations are following Table 2.

then divide it evenly according to the number of the intersected attention heads and add them to those heads. We denote this manner of leveraging *MTV-I* as *MTV-I-Distributional* (*MTV-I-D*). We also post the results of leveraging *MTV-I-D* in Table 3, where the results demonstrate that *MTV-I-D* can further achiever better performance than *MTV-I* in terms of language mismatch ratio, BLEU and COMET22DA.

6.2 Overall Results

To make readers get a better sense of the LLMs edited with our methods (*MTV-I-D* and *RPN-I*), we show the overall evaluation results for both our methods and traditional adaptation methods, including 5-Shot In-Context Learning (Brown et al., 2020) (5-Shot ICL), Low Rank Adaptation Tuning (Hu et al., 2022) (LoRA) and Full parameter Supervised Fine-Tuning (Alves et al., 2023) (Full-FT) for LLM-based MT in Table 4. Due to the page limit, we only post the performance on the metrics of language mismatch error ratio, repetition error ratio and BLEU score (We find that performance on COMET22 score is highly aligned with BLEU score). We observe that: (1) Applying the modified editing methods, *MTV-I-D* and *RPN-I* can generally reduce the error ratios for both language mismatch (**L**) and repetition (**R**) to a large degree, (2) The negative side-effect on the general translation quality (BLEU score, **B**) is minor (except when applying *MTV-I-D* under the setting of **zh**→**en**, with a -14.08% decrease percentage on BLEU score). It is noteworthy that applying *MTV-I-D* can even improve the general translation quality to a large extent on the settings of **en**→**de** (76.82%) and **en**→**zh** (24.64%) and (3) The performance of *MTV-I-D* and *RPN-I* can sometimes be comparable with (and even surpass) the traditional methods that adapt LLMs to the MT tasks, without additional requirements like long-context prompting and fine-tuning.

7 Conclusion

In the work we find that two types of errors, language mismatch and repetition, occur frequently when performing the machine translation tasks with LLMs, bringing severe negative effect on the translation quality. We investigate the potentials of leveraging model editing methods to mitigate these issues and find that directly adopting function vectors and knowledge neurons may either have limited improvement on the error ratio metrics or bring noteworthy negative effect on the metrics that evaluate general machine translation quality (e.g., BLEU score), which indicates that the located attention heads and FFN neurons might be too coarse to only affect the error ratios without hurting the translation quality. To this end, we propose to refine the located attention heads and neurons by fetching the intersection of the locating results under different language settings. Our empirical results suggest that the modified function vectors and knowledge neurons methods (*MTV-I-D* and *RPN-I*) can effectively reduce the aforementioned two types of errors and even bring a positive influence on the translation quality metrics in most settings, indicating that there indeed exist a small set of modules that are highly responsible for the language mismatch and the repetition errors meanwhile.

Limitations

Our work is based on open-source LLaMA series models (Touvron et al., 2023)[3]. However, the effectiveness of these findings on other models, such as the open-sourced Baichuan 2 (Yang et al., 2023) or the close-sourced GPT-4 (OpenAI, 2023), remains unknown.

The model editing methods used in this paper require computational resources proportional to the size of the large language model (LLM). When applying our methods to a larger model, more computational resources will be necessary to achieve improved results. Our focus is on high-resource language settings for machine translation (MT). However, the observations and conclusions may differ when applied to low-resource or non-English language pair settings (e.g., zh→de machine translation tasks)

We utilise automatic metrics for error and machine translation (MT) evaluation in our measurements. However, employing human-involved evaluations (Kocmi et al., 2023b) can offer a more profound understanding of the machine translation task with large language models (LLMs).

Ethics Statement

This paper utilizes a pre-trained large language model, with its training data sourced from web corpora that have not undergone ethical filtering. Consequently, it is capable of generating toxic content in the machine translation task (Wen et al., 2023). Moreover, we do not filter the source data or translation output in our work. Future research may build on our results to enhance the model, and we advocate for incorporating content supervision to prevent the dissemination of toxic content.

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A Dataset Information

Table 5 shows the detailed data size for $\mathcal{D}_{exps}$, $\mathcal{D}_{train}$ and $\mathcal{D}_{test}$. We use the WMT21 test set[4] as the $\mathcal{D}_{exps}$, WMT22 test set[5] as $\mathcal{D}_{train}$ and WMT23 test set[6] as$\mathcal{D}_{test}$.

The detailed data size for the K-shot ($K = 0, 1, 5$) setting is shown in Table 6. For all settings, we use the *lang prompt* as the prompt template (as shown in Section 3). For the Zero-Shot setting, we directly combine the source data with the *lang prompt*. For the One-Shot setting, we uniformly sample the data from $\mathcal{D}_{exps}$ based on the length of the example source to alleviate the potential length bias from prompt example(Zhang et al., 2023a). We use the most natural selection method for the Five-Shot setting by randomly selecting five examples from $\mathcal{D}_{exps}$.

Setting	$\mathcal{D}_{exps}$ Size	$\mathcal{D}_{train}$ Size	$\mathcal{D}_{test}$ size
en→de	1002	2037	557
de→en	1000	1984	549
en→zh	1002	2037	2074
zh→en	1948	1875	1976

Table 5: Data size of $\mathcal{D}_{exps}$, $\mathcal{D}_{train}$, $\mathcal{D}_{test}$ on four language settings.

Setting	$\mathcal{D}_0$ Size	$\mathcal{D}_1$ Size	$\mathcal{D}_5$ size
en→de ($\mathcal{D}_{train}$)	2037	12222	2037
de→en ($\mathcal{D}_{train}$)	1984	9920	1984
en→zh ($\mathcal{D}_{train}$)	2037	12222	2037
zh→en ($\mathcal{D}_{train}$)	1875	11250	1875
en→de ($\mathcal{D}_{test}$)	557	3342	557
de→en ($\mathcal{D}_{test}$)	549	2745	549
en→zh ($\mathcal{D}_{test}$)	2074	12444	2074
zh→en ($\mathcal{D}_{test}$)	1976	11856	1976

Table 6: Data size of Zero-Shot ($\mathcal{D}_0$), One-Shot($\mathcal{D}_1$) and Five-Shot($\mathcal{D}_5$) on four language settings. $\mathcal{D}_{train}$ and $\mathcal{D}_{test}$ represent the source data in the prompt.

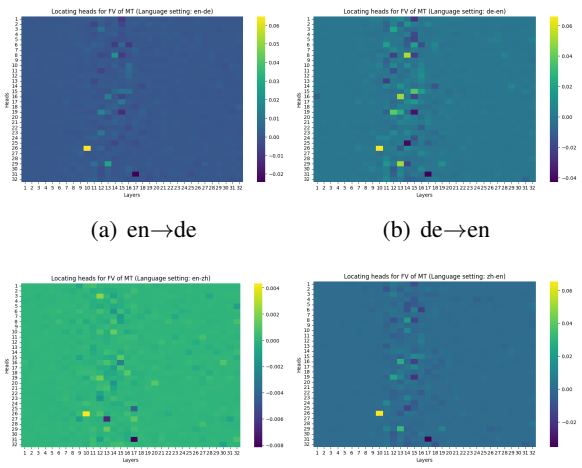
B Toolkits for evaluation

For the language mismatch detection, we use the Polyglot toolkit[7] to detect the language error. For repetition error, based on the definition of repetition error, we follow two rules to judge whether a translation result is repeated: (1) the generation length reaches the max_new_tokens setting[8]; (2) there exists a substring happening until the end of the generation. For the machine translation metrics, we use SacreBLEU(Post, 2018), Unbabel/wmt22-comet-da[9] and Unbabel/wmt22-cometkiwi-da[10] to do evaluation.

C The AIE values for all heads

Figure 4 shows the AIE values of all heads of LLaMA2-7B on en→de, de→en, en→zh and zh→en settings.

[4] https://github.com/wmt-conference/wmt21-news-systems
[5] https://github.com/wmt-conference/wmt22-news-systems
[6] https://github.com/wmt-conference/wmt23-news-systems
[7] https://github.com/aboSamoor/polyglot
[8] https://github.com/huggingface/tokenizers
[9] https://huggingface.co/Unbabel/wmt22-comet-da
[10] https://huggingface.co/Unbabel/wmt22-cometkiwi-da



(a) en→de (b) de→en

(c) en→zh (d) zh→en

Figure 4: Heatmaps of AIE values for attention heads in LLaMA2-7B for en→de setting (a), de→en setting (b), en→zh setting (c) and zh→en setting (d). The x-axis and y-axis refer to the layer and head, respectively. Brighter color refers to the head with larger AIE value.

D Results for direct adaptation

The complete results of direct adaptation on four language settings are shown in Table 7 (en→de), 8 (de→en), 9 (en→zh) and 10 (zh→de).

These tables show that the MT vectors can decrease the language mismatch ratio while the RP neurons help decrease repetition errors in all language settings.

Zero-Shot	**L(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.4524	12.6084	0.6113
+MT vectors	−92.46%	−0.81%	2.65%
+MT neurons	−11.1%	1.78%	0.15%
One-Shot	**R(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0141	24.9685	0.7279
+MT vectors	487.94%	−39.11%	−10.87%
+MT neurons	4.26%	−1.05%	−1.06%
+RP neurons	−27.66%	0.77%	−0.3%

Table 7: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language setting of **en→de**). ***Zero-Shot*** and ***One-Shot*** refer to using a zero-shot prompt (for language mismatch errors) and one-shot prompt (for repetition errors) for MT tasks. For evaluation metrics, **L**: Language mismatch ratio; **R**: Repetition ratio; **B**: BLEU and **C**: COMET22DA, where **B** and **C** mainly evaluate the general translation quality. For plain LLaMA2-7B, the results are absolute values; for LLaMA2-7B with editing methods, the results are relative **improvement percentages**.

Zero-Shot	**L(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0219	35.3448	0.7836
+MT vectors	−74.89%	−33.85%	−5.53%
+MT neurons	8.22%	0.03%	0.23%
One-Shot	**R(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0018	36.5445	0.7893
+MT vectors	727.78%	−33.62%	−4.38%
+MT neurons	22.22%	−0.35%	−0.11%
+RP neurons	−− %	−− %	−− %

Table 8: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language setting of **de→en**). The −− means the same result as the LLaMA2-7B since we do not detect any repetition on the training set under the same language setting. Notation and corresponding explanations can refer to Table 7.

Zero-Shot	**L(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.3269	16.3441	0.6567
+MT vectors	−70.05%	18.2%	5.07%
+MT neurons	−5.32%	3.16%	0.35%
One-Shot	**R(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0146	27.7798	0.7444
+MT vectors	162.33%	−15.29%	−4.0%
+MT neurons	5.48%	−4.28%	−0.28%
+RP neurons	−4.11%	0.55%	0.05%

Table 9: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language setting of **en→zh**). ***Zero-Shot*** and ***One-Shot*** refer to using a zero-shot prompt (for language mismatch errors) and one-shot prompt (for repetition errors) for MT tasks. Notation and corresponding explanations can refer to Table 7.

Zero-Shot	**L(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0486	17.1288	0.722
+MT vectors	−72.84%	−37.35%	−1.84%
+MT neurons	−18.72%	4.28%	−0.15%
One-Shot	**R(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0035	18.8714	0.7376
+MT vectors	482.86%	−23.07%	−1.68%
+MT neurons	0.0%	−0.35%	−0.03%
+RP neurons	−8.57%	0.07%	0.0%

Table 10: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language setting of **zh→en**). ***Zero-Shot*** and ***One-Shot*** refer to using a zero-shot prompt (for language mismatch errors) and one-shot prompt (for repetition errors) for MT tasks. Notation and corresponding explanations can refer to Table 7.

E Results for improved adaptation

Table 12, 11, 14 and 13 show the results for improved adaptation on en→de, de→en, en→zh and zh→en respectively.

Zero-Shot	**L(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0219	35.3448	0.7836
+MTV	**−74.89%**	−33.85%	**0.0036%**
+MTV-I	−58.45%	−4.84%	−5.53%
+MTV-I-D	−33.33%	**−0.53%**	−0.22%
One-Shot	**R(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0018	36.5445	0.7893
+RPN	−−%	−−%	−−%
+RPN-I	−−%	−−%	−−%

Table 11: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language settings of de→en for ***Zero-Shot*** and de→en for ***One-Shot***). The **–** means the results is the same as the LLaMA2-7B since there is no repetition cases in the $\mathcal{D}_{train}$. Other notations and abbreviations following Table 7.

Zero-Shot	**L(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.4524	12.6084	0.6113
+MTV	**−92.46%**	−0.81%	2.65%
+MTV-I	−80.15%	53.5%	15.51%
+MTV-I-D	−86.12%	**76.82%**	**16.02%**
One-Shot	**R(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0141	24.9685	0.7279
+RPN	−27.66%	**0.77%**	−0.3%
+RPN-I	**−27.66%**	0.35%	**−0.03%**

Table 12: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language settings of en→de for ***Zero-Shot*** and en→de for ***One-Shot***). Other notations and abbreviations following Table 7.

Zero-Shot	**L(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0486	17.1288	0.722
+MTV	**−92.46%**	−0.81%	2.65%
+MTV-I	−80.15%	53.5%	15.51%
+MTV-I-D	−86.12%	**76.82%**	**16.02%**
One-Shot	**R(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0035	18.8714	0.7376
+RPN	−8.57%	0.07%	**0.0%**
+RPN-I	**−25.71%**	**0.51%**	−0.04%

Table 13: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language settings of zh→en for ***Zero-Shot*** and zh→en for ***One-Shot***). Other notations and abbreviations are following Table 10.

Zero-Shot	**L(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.3269	16.3441	0.6567
+MTV	**−70.05%**	18.2%	5.07%
+MTV-I	−67.27%	19.08%	7.54%
+MTV-I-D	−69.9%	**24.64%**	**8.82%**
One-Shot	**R(↓)**	**B(↑)**	**C(↑)**
LLaMA2-7B	0.0146	27.7798	0.7444
+RPN	−4.11%	0.55%	**0.05%**
+RPN-I	**−19.18%**	0.01%	−0.23%

Table 14: Performance of LLaMA2-7B (and after applying model editing methods) on $\mathcal{D}_{test}$ (under the language settings of en→zh for ***Zero-Shot*** and en→zh for ***One-Shot***). Other notations and abbreviations are following Table 7.

F Implementation Details

For all machine translation results on LLMs, we only maintain the first line of the generation as the translation result based on the format of *lang prompt*. In the real translation process, we use batch generation techniques (batch size = 4) and set the maximum generation length of tokens to 400 with the Huggingface API[11] to do translations for any setting in this work.

Five-Shot For the Five-Shot setting, we directly use the $\mathcal{D}_5$ on LLaMA2-7B to run machine translation task without intervention.

LoRA fine-tuning LoRA (Low-Rank Adaptation)(Hu et al., 2022) is a parameter-efficient tuning technique generally used in natural language processing. In our work, we use the LoRA(Hu et al., 2022) method to align the LLaMA2-7B model to the machine translation task. For the fine-tuning data, we combine the data of all language settings from $\mathcal{D}_{train}$ into $\mathcal{D}_0$ and $\mathcal{D}_1$ for Zero-Shot setting and One-Shot setting respectively. Finally, we tune two LoRA models with the trl tool[12] with the self-supervised tuning method. We train one epoch with a rank of 64 and a learning rate of $2e^{-4}$ for both Zero-Shot and One-Shot. We use one NVIDIA A100 80GB Tensor Core GPU card for the SFT training; either the Zero-Shot or One-Shot costs less than a half day.

Full fine-tuning We use the same data and training tool in the LoRA setting for full fine-tuning. In the training process, we use the bfloat16 precious to train the model on one NVIDIA A100 80GB

[11] https://huggingface.co/

[12] https://github.com/huggingface/trl

Tensor Core GPU card for full fine-tuning with a lower learning rate $1e^{-6}$ compared to LoRA.

We claim there is still room for improvement in the LoRA or Full fine-tuning methods. However, a complete understanding of the mismatch and repetition error should also be evaluated on large-scale data, which is one of the following steps for our research.