Tuning Less, Prompting More: A Cost-Effective and Flexible Training and Inference Pipeline for Natural Language Transformation

Anonymous ACL submission

Abstract

Natural language transformation (NLT) tasks, such as machine translation (MT) and text style transfer (TST), require models to generate accurate and contextually appropriate outputs. However, existing approaches face significant challenges, including the computational costs of leveraging large pre-trained models and the limited generalization ability of fine-tuned smaller models. In this paper, we propose a novel framework that combines the flexibility of prompting with the cost-effectiveness of fine-tuning. Our method enhances small models by integrating In-Context Examples (ICE) retrieved from training data, enabling the model to better capture contextual information and align with user preferences. We further improve performance through hierarchical contrastive learning and dynamic preference inference mechanisms. Experimental results demonstrate that our approach outperforms existing methods, such as Supervised Instruction Tuning (SIT), Direct Preference Optimization (DPO), and Contrastive Preference Optimization (CPO), across both MT and TST tasks, providing a more efficient solution for resource-constrained environments.

1 Introduction

Recent advancements in natural language transformation (e.g., machine translation and text style transfer) have been significantly driven by large language models (LLMs) (Achiam et al., 2023; Grattafiori et al., 2024; DeepSeek-AI et al., 2024). Depending on whether model parameters are modified, existing approaches can be categorized into two main strategies: maintaining fixed parameters to elicit capabilities from large models through prompting, and modifying parameters to optimize performance of smaller models via fine-tuning. Prompting large models leverages their inherent flexibility and preserves their generalization capabilities without compromising the model's universal applicability (Hendy et al., 2023; Jiao et al., 2023b; Zhu et al., 2023). This approach allows for effective few-shot learning and adaptability across diverse tasks. On the other hand, fine-tuning smaller models, a trend gaining traction in recent studies, offers a cost-effective alternative by tailoring models to specific translation tasks (Zeng et al., 2023; Jiao et al., 2023a; Kudugunta et al., 2024; Zan et al., 2024; Li et al., 2024; Xu et al., 2023).

Despite their advantages, both methods exhibit significant drawbacks. While prompting large models can maintain high flexibility and generalization, it incurs substantial computational costs, which not only limits their practical deployment in resource-constrained environments but also leads to unavoidable performance inefficiencies (Xu et al., 2023). Conversely, fine-tuning small models for natural language transformation tasks involves a trade-off, where improving performance on specific tasks often comes at the cost of reduced generalization ability. This decline in generalization is particularly noticeable when the model encounters tasks it was not explicitly trained on. This phenomenon can be explained by the "prompt shift" effect (Li et al., 2023; Li and Hoiem, 2017; Lopez-Paz and Ranzato, 2022), where even small changes in the prompt format (without any change in meaning) can lead to a significant drop in response quality. Additionally, models are typically trained on parallel corpora, which limits their inference pattern to a [source text] -> [target text] mapping. This approach struggles to handle the polysemy that arises from contextual differences in translation, as too much contextual information can disrupt the format of the mapping. Additionally, the preference alignment techniques employed during the fine-tuning of small models struggle to handle data from multiple distributions and diverse contexts, further restricting their applicability.

To address these challenges, we propose a novel approach that combines the flexibility of prompting

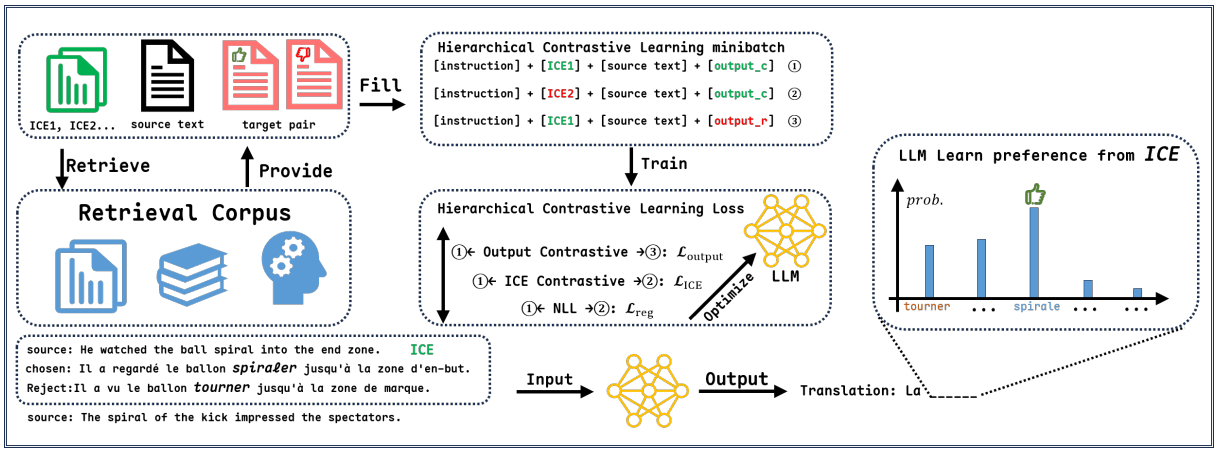

Figure 1: Framework for our Model Training and Inference. The diagram illustrates the three core components: (1) Data Augmentation through Contextual Similarity-based ICE Retrieval (top-left), (2) Hierarchical Contrastive Loss Design for fine-tuning model outputs (center), and (3) Dynamic Preference-Aware Inference for generating contextually relevant outputs (bottom-left). The arrows represent the flow of data and processes between these components.

with the cost-effectiveness of fine-tuning. Through an innovative training and inference pipeline, our method enables small models to extract sufficient contextual information from highly diverse In-Context Examples (ICE) within the prompting paradigm, learning fine-grained target preferences from similar contexts, thereby improving the quality of generated responses. Specifically, we retrieve similar samples from the training data, combine them into a few-shot learning format to enhance data points, and implement robustness mechanisms to handle the diversity of ICEs, further enhancing model performance through preference alignment design.

2 Related Work

In this section, we first reviewed the relevant research on Natural Language Transformation (NLT) tasks. Subsequently, we focused on two approaches based on large language models (LLMs): one involves leveraging the capabilities of general-purpose large models through the use of prompts, while the other entails fine-tuning smaller models for task-specific optimization. Finally, we analyzed the advantages, disadvantages, and challenges of both approaches in practical applications.

2.1 Natural Language Transformation

Natural Language Transformation (NLT) refers to the process of rewriting or adapting natural language texts at semantic, structural, or stylistic levels to fulfill specific task requirements or achieve desired functionalities. It encompasses a variety of tasks, including **machine translation** and **text style transfer**, which address diverse expressive objectives and application scenarios through flexible manipulation of linguistic elements. Building upon the foundational principles of Natural Language Transformation, recent advancements in large language models (LLMs) have catalyzed novel methodologies that leverage prompt-based paradigms to achieve flexible and context-aware language manipulation.

2.2 LLM-based Methods

Unlike traditional NLT approaches that often rely on task-specific architectures or explicit feature engineering, prompting-based methods exploit the intrinsic knowledge and generative capabilities of LLMs through carefully designed instructions or exemplars. This shift has enabled dynamic adaptation across diverse transformation tasks—from stylistic rewriting to domain-specific paraphrasing—by reformulating objectives as natural language prompts. Notably, techniques such as few-shot prompting, instruction tuning, and chain-of-thought reasoning have demonstrated remarkable efficacy in steering LLMs to disentangle semantic, structural, and stylistic nuances without requiring extensive fine-tuning.

In parallel to prompt-centric methodologies, recent efforts have prioritized specialized adaptation of compact language models through multi-stage fine-tuning strategies to address the unique demands of Natural Language Transformation (NLT). This paradigm typically begins with **continued pre-**

training, where models undergo domain-specific knowledge infusion via exposure to task-aligned corpora—such as stylistic parallel texts or multilingual translation pairs—to recalibrate their latent representations for transformation-centric objectives. Building upon this foundation, **instruction tuning** further optimizes models by training them on structured prompt-output pairs, enabling precise interpretation of diverse transformation intents. Finally, **preference alignment** mechanisms incorporate human or automated feedback—through techniques like reinforcement learning from human preferences or contrastive ranking—to refine outputs along critical dimensions such as stylistic consistency, lexical appropriateness, and domain-specific constraints. Collectively, this phased optimization framework allows smaller models to achieve task-aware specialization while maintaining computational tractability, thereby offering a viable alternative to large-scale LLMs in scenarios requiring strict deployment efficiency or niche-domain expertise.

2.3 Preference Alignment

Building upon the foundational stages of domain adaptation through continued pretraining and instruction tuning, preference alignment emerges as a critical mechanism to bridge the gap between model capabilities and human-centric quality requirements. While the former stages equip models with task-specific knowledge, the latter ensures that outputs adhere to nuanced desiderata: stylistic coherence, lexical precision, and context-sensitive appropriateness, which are often underspecified in textual instructions. This subsection systematically examines cutting-edge approaches to preference alignment, analyzing their technical innovations in reconciling algorithmic optimization with human judgment across diverse NLT scenarios.

Three noteworthy methods for preference alignment include Proximal Policy Optimization (PPO), Direct Preference Optimization (DPO), and Contrastive Preference Optimization (CPO). PPO sets a high-level goal for the alignment process: to maximize the "satisfaction" of a reward model trained on carefully organized preference data. While effective, this approach involves a complex pipeline, including reward modeling and iterative policy updates. In contrast, DPO and CPO bypass the need for explicit reward modeling through skillful equivalent transformations. These methods directly utilize the general tendencies of the collected preference dataset as the alignment target, thereby simplifying the alignment process. Together, these methods provide a range of approaches for aligning model outputs with human preferences, each offering unique advantages depending on the complexity and constraints of the task at hand.

3 Methods

In this section, we present a detailed description of our framework, which comprises three core components (as illustrated in **Figure 1**): (1) Contextual Similarity-based ICE Data Augmentation, (2) Hierarchical Contrastive Loss Design that guides the model to disentangle fine-grained semantic features from augmented data, and (3) Dynamic Preference Inference Mechanism that enhances model outputs through user-customized or retrieval-augmented preference sample prompts. The subsequent sections will systematically elaborate on the design principles and implementation details of each component.

3.1 Contextual Similarity-Based ICE Augmentation via Retrieval

To address the limitations of rigid [source→target] mappings in conventional fine-tuning, we introduce a retrieval-augmented paradigm that enriches training data with explicit preference signals through in-context exemplars. The core objective is to enable small models to resolve contextual ambiguity by learning from semantically aligned preference pairs, thereby emulating the few-shot reasoning capabilities of large language models. Our approach constructs augmented data points by retrieving semantically congruent exemplars from the training corpus based on source text similarity. This is achieved by computing cosine distances between sentence embeddings derived from a pre-trained language model, ensuring that the retrieved in-context examples (ICEs) share comparable linguistic patterns and domain characteristics with the target source.

Each retrieved ICE (ICE source, ICE chosen, ICE rejected) serves as explicit preference evidence, forming an augmented input structure: [ICE source, ICE chosen, ICE rejected; current source] → current chosen. This format allows the model to simultaneously learn from both the target instance and its contextual neighbors, reinforcing preference consistency across analogous contexts. By integrating ICEs, the model is exposed to di-

verse yet semantically aligned examples, enabling it to generalize beyond the narrow [source→target] mapping and capture fine-grained preference patterns conditioned on contextual semantics.

The methodology is designed to be flexible and extensible. While our implementation utilizes in-corpus retrieval for experimental consistency, the architecture inherently supports integration with external knowledge bases through unified embedding alignment. Additionally, the approach incorporates robustness mechanisms by prioritizing high-similarity exemplars (top-k retrieval) and introducing adversarial negative samples through lexical substitution, mitigating potential noise from suboptimal retrievals. This retrieval-enhanced paradigm fundamentally repositions small models from passive pattern memorizers to active context interpreters, laying a critical foundation for subsequent preference alignment learning.

3.2 Hierarchical Contrastive Learning with Dual ICE Augmentation

Building upon the retrieval-augmented samples $[ICE, \text{prompt}, \text{chosen}, \text{reject}]$ from the previous step, we introduce a hierarchical contrastive objective that operates at both the model output and ICE levels. First, to strengthen the model's ability to distinguish between preferred and rejected outputs, we apply contrastive learning between $[ICE, \text{prompt}, \text{chosen}]$ and $[ICE, \text{prompt}, \text{reject}]$. By emphasizing the difference between the chosen and rejected outputs under otherwise identical contextual cues, this step enhances the model's ability to internalize explicit preference signals. Crucially, this contrastive signal helps the model capture more subtle features that drive user-preferred outputs, moving beyond simple pattern matching. The contrastive loss at the output level can be expressed as:

$$\mathcal{L}_{\text{output}} = -\log \sigma \left(\beta \log \frac{\pi_\theta(y_c|ICE_1, x)}{\pi_\theta(y_r|ICE_1, x)} \right) \quad (1)$$

Where, π_θ represents the current model, y_c and y_r stand for chosen output and rejected output. β is a hyperparameter, and in the experiment, we set it to 0.15.

Next, to further enhance the model's robustness to variations in the quality of ICE selections, we introduce a second set of exemplars (ICE_2) and construct new augmented input pairs: $[ICE_1, \text{prompt}, \text{chosen}]$ and $[ICE_2, \text{prompt}, \text{chosen}]$. This dual ICE augmentation enforces an additional contrastive objective, encouraging consistent representations of the same target across different in-context exemplars. By aligning semantically similar but potentially divergent examples, this approach mitigates the impact of retrieval noise, ensuring that the learned preferences remain robust despite contextual changes. The contrastive loss at the ICE level can be formulated as:

$$\mathcal{L}_{\text{ICE}} = \text{Sim}[\pi_\theta(ICE_1; x; y_c); \pi_\theta(ICE_2, x; y_c)] \quad (2)$$

where $\pi_\theta(ICE_1; x; y_c)$ represents the last token's logits after model computing, and Sim() means cosine similarity function.

Finally, to stabilize learning and maintain a coherent preference distribution, we introduce a regularization term based on the negative log-likelihood (NLL) between $[ICE_1, \text{prompt}, \text{chosen}]$ and $[ICE_2, \text{prompt}, \text{chosen}]$. This regularization term can be represented as:

$$\mathcal{L}_{\text{reg}} = \text{NLL}[\pi_\theta(y_c|ICE_1, x)] + \quad (3)$$

$$\text{NLL}[\pi_\theta(y_c|ICE_2, x)] \quad (4)$$

The overall training objective combines these three loss components through a weighted to balance their contributions during optimization. By integrating output-level discrimination, ICE-level consistency, and distributional regularization, the unified loss function ensures the model learns robust preference patterns while maintaining generation stability. The total loss is defined as:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{output}} + \min(\frac{\mathcal{L}_{\text{reg}}}{\mathcal{L}_{\text{ICE}}}, \lambda)\mathcal{L}_{\text{ICE}} + \mathcal{L}_{\text{reg}} \quad (5)$$

where λ is weighting coefficients that control the relative strength of each objective. This balanced formulation allows the model to simultaneously optimize for preference discrimination, contextual robustness, and distributional coherence. In practice, we find equal weighting ($\lambda = 1.0$) provides stable convergence, though domain-specific tuning may further enhance performance.

Through this layered contrastive framework, the model develops a more comprehensive and robust understanding of user-driven preference patterns, laying a strong foundation for subsequent dynamic

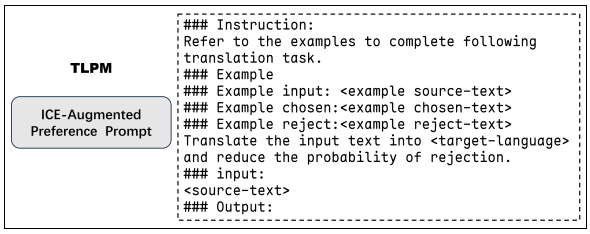

Figure 2: Inference Prompt in Machine Translation

preference inference tasks. The modular design of this approach allows for easy adaptation and expansion to other domains, making it both flexible and extensible for future research and applications.

3.3 Dynamic Preference-Aware Inference with Retrieval-Augmented Prompts

Following the hierarchical contrastive learning process described in the previous section, we now turn our attention to the inference phase, where the trained model is leveraged for dynamic preference-driven tasks. In this stage, the model benefits from the contextualized training achieved through the integration of ICEs and contrastive learning, enabling it to generate outputs aligned with user preferences in various settings.

For inference, the model receives a source text as input, which serves as the foundation for generating the desired output. To tailor the output to specific preferences or contextual requirements, we first perform a dynamic ICE customization step. This involves retrieving and selecting relevant in-context exemplars based on the particular scenario or user-defined preferences. These exemplars are then incorporated into the input structure, forming an augmented inference sample in the format: [ICE, source text]. This retrieval-augmented input ensures that the model's reasoning is guided by contextually appropriate, preference-aligned examples, effectively integrating the learned patterns from the training phase. By feeding the model with these augmented samples, which are dynamically assembled according to the preferences associated with the task at hand, the model is capable of producing outputs that reflect not only the linguistic properties of the source text but also the underlying preference structure inferred during training. This mechanism allows for seamless adaptation of the model to diverse inference scenarios, enhancing its flexibility and responsiveness to varying user needs and contextual nuances.

The dynamic preference-aware inference process ensures that the model's outputs are not only accurate but also personalized and contextually relevant, providing a robust solution for real-world applications where user preferences and context play a critical role in the decision-making process. This approach, which builds on the foundation of hierarchical contrastive learning and retrieval-augmented inputs, thus enables the model to generate high-quality outputs that align with nuanced preferences, facilitating more sophisticated and tailored language generation tasks.

4 Experiments

To comprehensively evaluate the effectiveness of our proposed framework, we conduct extensive experiments across two dimensions: (1) comparing performance against state-of-the-art baselines, and (2) analyzing the robustness of our hierarchical contrastive learning mechanism through ablation studies. All experiments are designed to answer the key research question: How does our retrieval-augmented training inference paradigm improve preference alignment compared to conventional fine-tuning?

4.1 Data

We conducted experiments on the MT and TST tasks. In this section, we will provide a detailed explanation of how we obtained, processed, and assembled our data.

4.1.1 Preference Data

For MT, we conducted the experiments on the **ALMA-R-Preference** dataset which (Xu et al., 2024) released, and selected the chosen and rejected translations for the target language based on the average quality of each data item. We also performed supplementary experiments on translation tasks involving other low-resource languages using the Flores-200 dataset (Team et al., 2022). We transformed the Flores-200 dataset into a pairwise preference dataset using GPT-4o to generate candidate responses, and employed a Feedback from Inductive Biases method (Jiang et al., 2024) to construct the preference direction, ensuring alignment with the test set provided in the Flores-200 dataset. For the TST task, we directly used an open-source preference dataset[1]. This dataset is designed to convert modern language into the writing style of specified literary works, encompassing idiomatic

[1]https://github.com/stylellm/stylellm_models

Table 1: The main result in Translating to English (xx→en). Our methods significantly outperform all comparable methods. The dark blue boxes indicates a significant improvement compared to their original versions , while light blue boxes represents only a small but noticeable enhancement. All red colors indicate a slight decrease in performance.

Methods	de		zh		ru		cs		ind	
	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET
SFT	33.12	93.67	25.13	90.45	39.12	90.42	41.22	86.54	31.05	91.86
DPO	31.99	93.24	25.17	89.94	39.11	89.16	42.15	86.70	31.58	91.92
CPO	32.74	94.72	26.32	91.73	38.26	91.85	43.13	89.91	30.27	92.60
Ours	34.21	96.31	26.22	92.86	39.13	93.44	41.47	91.37	37.47	94.71

Table 2: The main result in Translating from English (en→xx).

Methods	de		zh		ru		cs		ind	
	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET
SFT	30.25	88.81	27.94	87.94	27.12	88.37	26.22	87.62	25.93	89.48
DPO	29.50	90.03	27.33	88.23	26.32	87.03	26.25	88.68	25.41	89.43
CPO	30.54	90.16	24.87	89.85	25.14	89.63	27.13	88.73	27.21	90.04
Ours	31.22	91.74	26.33	90.51	27.22	90.47	29.47	89.53	26.01	90.13

vocabulary, syntactic structures, and rhetorical devices. The target literary works include China's Four Great Classical Novels. Although it belongs to the same language, it is a dataset with four distinctly different task scenarios, where the expected preference for the same sentence varies in each scenario.

4.1.2 Data preparation

In the implementation of the retrieval component, we use **SentenceTransformer** with the "**xlm-r-bert-base-nli-stsb-mean-tokens**" model (Reimers and Gurevych, 2019) to generate dense vector representations of input queries. The model is configured with a maximum sequence length of 512. The generated embedding vectors serve as the foundation for retrieval, effectively capturing semantic relationships within the source text. To enable efficient similarity retrieval, we construct an IVF-Flat clustering index based on **Faiss** (Douze et al., 2024). The embedding space is partitioned into 50 clusters to facilitate scalable retrieval. In our experiments, we use the original training set as the retrieval space. For each sample point, we identify the two most similar samples based on its source text and designate them as ICE_1 and ICE_2.

4.2 Experiments Setting

In this section, we present the baselines used in our comparative experiments, along with detailed experimental configurations and the hardware setup. Following this, we introduce the baselines chosen for our experiments and explain the rationale behind these selections.

4.2.1 Baseline

SIT Using Supervised Instruction Tuning to adapt large language models to specific downstream tasks is a fundamental approach. Its effectiveness has been validated through extensive practical experiments. Therefore, SIT on prefer data serves as the first baseline in our experiments.

DPO Direct Preference Optimization is a method designed to directly optimize models for preference alignment, focusing on aligning model outputs with user preferences rather than traditional loss functions. It has gained widespread use in the field of preference learning, especially in scenarios where the goal is to predict or rank items based on user preferences. DPO has become a popular choice in many preference alignment applications. Before applying the DPO method, we conducted preliminary training with the selected data to simulate the typical pipeline for preference alignment using DPO.

CPO We also compared the commonly used preference alignment methods in the machine translation field. Contrastive Preference Optimization is derived from the same optimization goal but reflect different training objectives with DPO. Therefore, these two methods serve as the primary comparative methods for the evaluation of preference alignment.

4.2.2 Training Details

Our experiment primarily focuses on comparing fine-tuning methods rather than specific base models. We conducted our main experiments on widely used open source LLMs(Touvron et al., 2023; Dubey et al., 2024). We used an earlier version, LLaMA2-13B and LLaMA3-8B, for our experiments and present the main result in it.

Training with LoRA For all models, we employ the AdamW optimizer with a learning rate of 2e-5. We fine-tuned the models using a batch size of 8, across 3 epochs, and set the maximum sequence length to 666 tokens to ensure efficient handling of longer input sequences. The LoRA technique is utilized, with a rank of 32, and the fine-tuning process only updates the weights of the added LoRA parameters, which introduce an additional 24M parameters to the base model's original 13B parameters. Regarding the model architecture, the following target modules are updated during training: q_proj, k_proj, v_proj, and o_proj, while other projection layers, including gate_proj, down_proj, and up_proj, remain fixed. To prevent overfitting and enhance generalization, we apply a dropout rate of 0.05 during the training phase. The combination of these hyperparameters ensures efficient adaptation of the model to the specific task while minimizing the computational overhead added by the LoRA modifications. We adhere to the default β value of 0.1 as suggested by Rafailov et al. (2024)

4.3 result

We present the primary result of MT in Table 1 and Table 2. Our evaluation metrics include both statistical and neural metrics (Papineni et al., 2002; Rei et al., 2020), but we place a primary emphasis on neural metrics, using statistical metrics only as a reference with a limited level of confidence. For neural metrics, we adopted the XCOMET series models [2], and for statistical metrics, we used BLEU. For all metrics, we calculate result with Chosen term of test data point. In translation tasks in five languages, including German, Chinese, Russian, Czech, and Indonesian, Our methods achieved an average score of 92.10 of XCOMET, CPO averaged 90.92, DPO 89.43, and SIT 89.51.

For TST, we present the primary results in Figure 3. For this evaluation task, we adopted the LLM-as-Judge method[3] as the main evaluation metric, leveraging the capabilities of large language models to assess the quality, fluency, and stylistic consistency of the generated text. The LLM-as-Judge approach provides a more nuanced and context-aware evaluation, making it particularly suitable for capturing the subtle nuances in style transfer tasks. The evaluation results are presented in terms of win rate, which is calculated based on pairwise comparisons conducted by LLM-as-Judge. To ensure the reliability and robustness of the evaluation, each pairwise comparison was performed twice independently. Only when the two independent assessments yielded consistent results was a winner determined; otherwise, the outcome was considered a tie. This rigorous approach minimizes potential biases and enhances the credibility of the evaluation process.

Figure 3: The experimental results of the TST task, evaluated through LLM-as-Judge, show that our method achieves better transfer consistency with the target style.

5 Analysis

In this section, we conduct ablation experiments and analyses. Through ablation experiments, we demonstrate the effectiveness of our hierarchical contrastive design. Additionally, through comprehensive analysis, we provide a theoretical explanation of why our approach achieves good results.

Ablation Study To systematically validate the effectiveness of our proposed hierarchical contrastive learning framework, we conducted ablation experiments by progressively removing the loss terms defined in Section 3.2. The experiments were carried out on the machine translation (MT) task, with a comprehensive quality evaluation using the XCOMET metric. As shown in Table 3 and Table 4, removing the ICE-level contrastive loss leads to a performance drop, which demonstrates the importance of maintaining consistency across different contextual examples. Further removal of the output-level contrastive loss also results in a performance decline, indicating its crucial role in

[2] we use XCOMET-XL

[3] We use deepseek-chat as the judge model

Table 3: The ablation result in Translating to English (xx→en).

Methods	de		zh		ru		cs		ind	
	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET
Ours	34.21	96.31	26.22	92.86	39.13	93.44	41.47	91.37	37.47	94.71
- $\mathcal{L}_{\text{ICE}}$	35.33	95.96	25.89	93.13	37.55	92.35	43.34	90.67	30.11	93.67
- $\mathcal{L}_{\text{output}}$	31.19	95.43	25.78	91.76	35.54	91.97	40.13	88.72	35.02	94.39

Table 4: The ablation result in Translating from English (en→xx).

Methods	de		zh		ru		cs		ind	
	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET	BLEU	XCOMET
Ours	31.22	91.74	26.33	90.51	27.22	90.47	29.47	89.53	26.01	90.13
- $\mathcal{L}_{\text{ICE}}$	31.41	90.66	25.89	90.23	26.20	90.11	27.88	89.27	23.73	89.26
- $\mathcal{L}_{\text{output}}$	29.96	89.91	25.78	88.37	27.93	89.13	28.25	87.28	25.37	89.21

distinguishing subtle differences between selecting and rejecting responses.

Perturbation Analysis We also conducted perturbation experiments on the similarity ranking of the ICE used during retrieval in the test phase to investigate the impact of ICE quality on the results. Specifically, we experimented with four types of ICE: rank1 (the most similar to the source text), rank2, rank3 (less similar), and a fixed ICE that bypassed the retrieval process entirely. We performed ablation experiments on the MT (machine translation) task, and the specific results are shown in Table 5. From the results, we observed a clear trend: the performance of the model improved significantly when the ICE was more similar to the source text. Specifically, rank1 ICE, which exhibited the highest similarity to the source text, led to the most substantial performance gains, while the fixed ICE, which lacked similarity-based retrieval, resulted in the least improvement. This demonstrates that the quality and relevance of the ICE, particularly its similarity to the source text, play a critical role in enhancing model performance.

Table 5: Performance trend for different rank of example

Model	ICE1	ICE2	ICE3
XCOMET	95.25	94.67	94.59
	Constant ICE	**SIT**	**CPO**
XCOMET	93.60	92.13	93.62

6 Conclusion

This paper presents a novel approach combining prompting and fine-tuning for natural language transformation (NLT) tasks, specifically in machine translation (MT) and text style transfer (TST). The proposed method integrates small models with retrieved in-context examples (ICE) based on contextual similarity, allowing them to leverage contextual information and user preferences. By combining contextual augmentation with hierarchical contrastive learning, the approach enhances the flexibility of small models while maintaining efficiency in resource-constrained environments. Our experiments demonstrate that this hybrid framework outperforms traditional methods, such as Supervised Instruction Tuning (SIT), Direct Preference Optimization (DPO), and Contrastive Preference Optimization (CPO), particularly in terms of alignment with user preferences.

In future work, the framework can be further extended to other natural language processing tasks, optimizing both the retrieval mechanism and the contrastive learning approach to improve generalization and robustness.

Limitation

While our proposed framework successfully integrates prompting and fine-tuning for efficient context-aware language transformation, it exhibits several limitations that the method depends on high-quality retrieval, faces scalability challenges with large embeddings, and struggles with balancing the diversity and relevance of retrieved examples for effective model performance.

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