Personalized LLM Decoding via Contrasting Personal Preference

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Abstract

As large language models (LLMs) are progressively deployed in various real-world applications, personalization of LLMs has become increasingly important. While various approaches to LLM personalization such as prompt-based and training-based methods have been actively explored, the development of effective decoding-time algorithms remains largely overlooked, despite their demonstrated potential. In this paper, we propose COPE (**Co**ntrasting **Pe**rsonal Preference), a novel decoding-time approach applied after performing parameter-efficient fine-tuning (PEFT) on user-specific data. Our core idea is to leverage reward-guided decoding specifically for personalization by maximizing each user's implicit reward signal. We evaluate COPE across five open-ended personalized text generation tasks. Our empirical results demonstrate that COPE achieves strong performance, improving personalization by an average of 10.57% in ROUGE-L,without relying on external reward models or additional training procedures.[1]

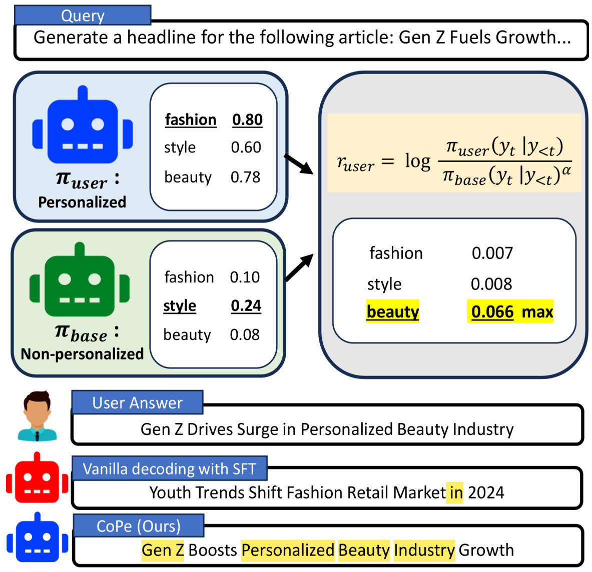

Figure 1: **Implicit reward maximization via contrastive preference**. Under an implicit reward model that leverages the interaction between a personalized and a non-personalized generic model, generated texts better align with user preferences. The highlighted text marks words that overlaps with the gold answer.

1 Introduction

Personalization of Large Language Models (LLMs) (Achiam et al., 2023; Team et al., 2023; Anthropic, 2024; Touvron et al., 2023), which refers to the process of aligning model outputs with individual user preferences, has received growing attention as LLMs are increasingly deployed in real-world applications such as writing assistants (Mysore et al., 2024), content recommendation (Zhang et al., 2024), and review generation (Peng et al., 2024). Prompt-based personalization (Santurkar et al., 2023; Hwang et al., 2023), which augments a user query by retrieving prior interactions or constructing a summarized user profile, is arguably considered as one of the most straightforward approaches. However, its effectiveness is often limited by the absence of direct learning from user data. In contrast, training-based personalization (Zhao et al., 2024; Kim and Yang, 2025) captures user preferences more effectively by updating model parameters, but it also suffers from challenges such as catastrophic forgetting and increased computational costs. To mitigate these limitations, recent works such as One PEFT per User (Tan et al., 2024) have demonstrated that lightweight parameter-efficient fine-tuning (PEFT) offers a viable solution for personalizing LLMs (Tan et al., 2025; Zhang et al., 2025a; Kim et al., 2025b). Unlike prior works mentioned above, we turn to a new perspective for effective LLM personalization.

In this work, we introduce COPE (**Co**ntrasting **Pe**rsonal preference), a new paradigm for LLM

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[1]Code is available at https://github.com/cleverscent/CoPe.

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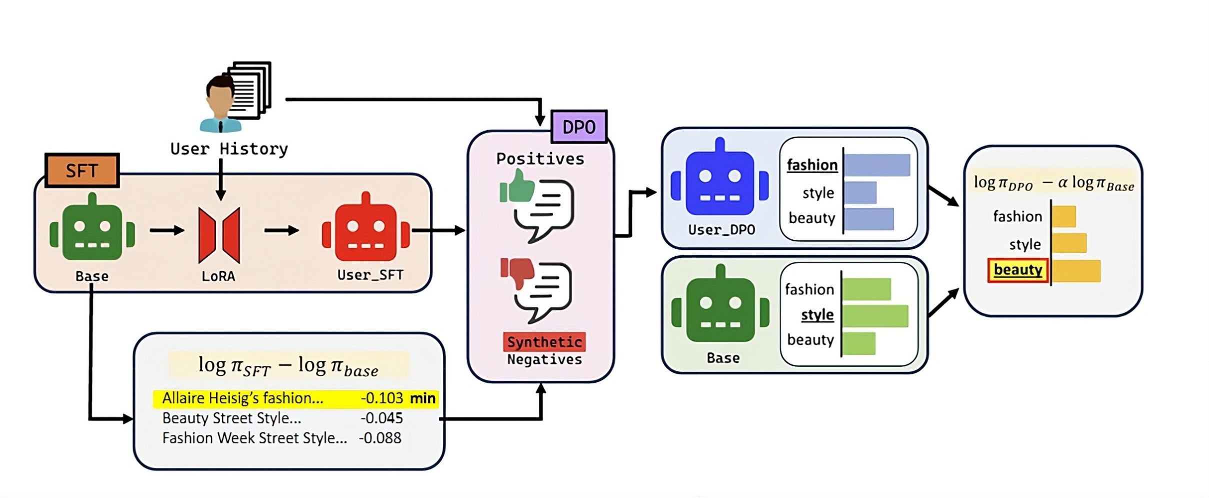


Figure 2: **Illustration of CoPE** (**Co**ntrasting Preference for **Pe**rsonalized LLM Decoding). The training pipeline (left) builds an expert user model via Direct Preference Optimization (DPO) with synthetic negatives. The reward-guided decoding method (right) contrasts this user model with a base model at the token level, maximizing implicit user reward during both training and decoding for improved personalization.

personalization that operates at the decoding stage, applied after PEFT on user-specific data. At a high level, CoPE is a form of *reward-guided decoding* (Deng and Raffel, 2023; Khanov et al., 2024; Lightman et al., 2024), an approach that effectively steers LLM outputs toward desired properties (*e.g.*, improved reasoning) by maximizing a reward function, adapted specifically for personalizing LLMs across varying contexts and user goals.

Unlike conventional reward-guided decoding methods, CoPE does not require an external reward model to estimate rewards. Instead, it leverages the implicit user reward signal, which can be efficiently approximated using the likelihoods from both the PEFT-tuned model and the original base model. Building on our key insight which connects this implicit reward to the objective of contrastive decoding (Li et al., 2023),we can implement the proposed CoPE easily (see overview in Figure 2).

In addition, we further enhance PEFT for LLM personalization by encouraging the model to better capture the implicit user reward. The core idea is to contrast implicit rewards between a *positive* response (provided by the user) and a *negative* response (unlikely to be from the user, *e.g.*, from other users), using Direct Preference Optimization (DPO) (Rafailov et al., 2023). To avoid the practical and privacy challenges of relying on data from other users, we synthesize negative responses by generating outputs with low implicit rewards via Best-of-N sampling (Gui et al., 2024). This training method not only improves the effectiveness of PEFT, but also enhances the performance of our proposed reward-guided decoding by enabling more accurate modeling of the implicit user reward. An overview of the pipeline is shown in Figure 2.

We demonstrate the effectiveness of CoPE with experiments in five different personalized open-ended text generation tasks from Language Model Personalization (LaMP) (Salemi et al., 2024) and LongLaMP (Kumar et al., 2024) benchmarks. Specifically, CoPE achieves an average relative improvement of 10.57% in ROUGE-L across all tasks, compared to the task-finetuned model. Notably, CoPE also outperforms a simply personalized model that lacks the contrastive mechanism, with an average ROUGE-L gain of 5.67% across tasks. Furthermore, the effectiveness of CoPE is well-generalized across different scales and types of state-of-the-art LLMs. Our robust experimental results show that the implicit reward maximization of CoPE further enhances alignment with individual user preferences. Together, these findings highlight CoPE as a promising approach for scalable and effective LLM personalization.

2 Related Works

LLM personalization. Given the diversity of user goals and preferences, various approaches to personalization of LLM have been explored. One common strategy is prompt-based personalization, wherein techniques such as retrieval-augmented generation (RAG) (Lewis et al., 2021) and prompt-augmented generation (PAG) (Richardson et al.,

2023) dynamically inject user-specific context into each prompt at inference. However, these methods lack parametric memory and rely entirely on prompt construction, making them vulnerable to context length limitations and insufficient grounding. On the other hand, training-based personalization methods, which fine-tune the model on user-specific data, have demonstrated superior performance in capturing user preferences compared to prompting-based approaches (Zhao et al., 2024; Zhuang et al., 2024). Nevertheless, even these methods face several limitations. Firstly, these methods are computationally intensive, as they involve modifying model parameters. In fact, in the worst case, frequent retraining may be necessary to reflect evolving user preferences (Madotto et al., 2021). Moreover, these methods are susceptible to catastrophic forgetting, a phenomenon in which adapting to new user data can lead the model to forget previously learned preferences or even general knowledge (McCloskey and Cohen, 1989; de Masson d'Autume et al., 2019).

A recent and practical method to address these limitations is the utilization of lightweight parameter-efficient fine-tuning (PEFT), which offers an effective and scalable approach to personalizing LLMs (Zhang et al., 2024, 2025b). Meanwhile, personalization at the decoding stage remains largely unexplored in existing methods. Motivated by this gap, we aim to address the aforementioned limitations through a decoding-based approach to personalization.

LLM decoding. Various decoding strategies have been explored and applied in LLMs to boost their performance. For instance, contrastive decoding has demonstrated strong effectiveness not only in open-ended text generation (Li et al., 2023), but also in reasoning (O'Brien and Lewis, 2023), retrieval-augmented generation (RAG) (Shi et al., 2023), and even multi-modal generation (Leng et al., 2023). On the other hand, reward-guided decoding has emerged as another promising approach, aiming to improve alignment and reasoning capabilities directly at the decoding stage, without additional model training. To further explain, reward-guided decoding guides the generation process using reward signals, offering a lightweight yet effective alternative for steering outputs toward desired behaviors (Deng and Raffel, 2023; Lightman et al., 2024). In fact, adaptive reward shaping, as proposed by Khanov et al. (2024), has also been shown to improve sample efficiency during decoding. Despite the growing interest in both decoding strategies and personalization, there is no prior work that effectively leverages decoding methods for personalization due to the challenge of modeling separate rewards for each user. In this aspect, we propose the first guided decoding approach for personalization that does not require any external reward models. Specifically, our method can be easily implemented using contrastive decoding, thereby enabling more practical and scalable deployment in real world settings.

Preference learning. Preference learning is an approach that ensures alignment with human or task-specific preferences by leveraging relative feedback between outputs, rather than relying on absolute labels. One traditional approach to preference learning is Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022), which involves fitting a reward model based on human-labeled comparisons and optimizing model policies through reinforcement learning. However, RLHF often requires complex and costly training procedures. To address this limitation, recent methods such as Direct Preference Optimization (DPO) (Rafailov et al., 2023) simplify the process by directly fine-tuning models through binary classification between preferred and dispreferred outputs.

Building on these advances, we propose a personalized fine-tuning method that integrates preference learning by treating user profile responses as positive examples and non personalized outputs as negative examples. This training formulation supports contrastive decoding, due to the fact that maximization of implicit user reward is plausible both in the training and decoding section. In other words, this conceptual alignment between preference learning and contrastive decoding ensures consistency between training and inference, enabling more effective personalization without external reward models or additional training procedures.

3 CoPE: Contrasting Preference for Personalized LLM Decoding

In this section, we present our new decoding framework for LLM personalization by **Co**ntrasting **P**ersonal preference (CoPE). Our key idea is incorporating *implicit reward signals* for user preference to guide both training and inference. We first present our problem setup in Section 3.1. Next, we present the proposed decoding scheme, CoPE, in

Section 3.2. Lastly, in Section 3.3, we present our training scheme to further improve PEFT for personalization, by explicitly maximizing user reward based on the synthetic negative response.

3.1 Preliminary

Let us first assume that we have the historical interaction data $H_{\texttt{user}} = \{(x^i, y^i)\}_{i=1}^N$ for a target user. Then, for a given input query x, the goal of LLM personalization is to generate a personalized output y from LLM π that aligns with the user's preferences and behaviors exhibited in $H_{\texttt{user}}$. A representative approach for LLM personalization is to adapt a generic pre-trained LLM $\pi_{\texttt{base}}$ using parameter-efficient fine-tuning (PEFT) techniques, such as LoRA (Hu et al., 2021).

Formally, let $\Delta_{\texttt{user}}$ denote the user-specific PEFT module.[2] The personalized model is then defined as $\pi_{\texttt{user}} = \pi_{\texttt{base}} + \Delta_{\texttt{user}}$, such that only $\Delta_{\texttt{user}}$ is optimized using the user's data $H_{\texttt{user}}$. For example, Tan et al. (2024) optimizes $\Delta_{\texttt{user}}$ on $H_{\texttt{user}}$ via conventional supervised fine-tuning (SFT) that minimizes cross-entropy between the output of $\pi_{\texttt{user}}(x^i)$ and ground-truth label y^i. After optimizing $\Delta_{\texttt{user}}$, $\pi_{\texttt{user}}$ is expected to generate the responses that align with the user's preferences.

3.2 Optimizing personal preference via contrastive decoding with PEFT

Assume that we have access to a base model $\pi_{\texttt{base}}$ and a personalized model $\pi_{\texttt{user}}$. Then, to generate a response y that better aligns with the user's preferences for a given test query x, CoPE adopts a reward-guided decoding strategy that contrasts the token-level likelihoods under these two models.

Let $y_{<t} = (y_1, \dots, y_{t-1})$ denote the partial output sequence at decoding step t. Then, following Li et al. (2023), we first define a plausibility-constrained candidate set of next tokens as:

$$\mathcal{V}_{\text{head}}^t = \{y_t \in \mathcal{V} \,|\, \pi_{\texttt{user}}(y_t \mid y_{<t}) \geq \tau_t\}, \quad (1)$$

where $\tau_t := \tau \cdot \max_{w \in \mathcal{V}} \pi_{\texttt{user}}(w \mid y_{<t})$ is an adaptive threshold determined by a hyperparameter $\tau \in [0, 1]$ and $\mathcal{V}$ denotes the vocabulary for $\pi_{\texttt{user}}$. For each candidate token $y_t \in \mathcal{V}_{\text{head}}^t$, we compute an implicit user reward by contrasting its likelihoods under the personalized and base models:

$$r_{\texttt{user}}(y_t) = \log \frac{\pi_{\texttt{user}}(y_t \mid y_{<t})}{\pi_{\texttt{base}}(y_t \mid y_{<t})^{\alpha}}, \quad (2)$$

where $\alpha \geq 0$ is a contrastive weight hyperparameter. This reward encourages the selection of tokens that are strongly preferred by the personalized model while being penalized under the base model, yields the outputs that are both user-aligned and distinctive. Finally, the next token y_t^* is selected which maximizes the implicit user reward:

$$y_t^* = \arg \max_{y_t \in \mathcal{V}_{\text{head}}^t} r_{\texttt{user}}(y_t). \quad (3)$$

Rationale behind implicit user reward. Here, we present the theoretical intuition behind our proposed implicit user reward $r_{\texttt{user}}$ (Eq. 2). To this end, we revisit the concept of *implicit reward* introduced in DPO (Rafailov et al., 2023), which has been widely adopted in the LLM alignment literature (Chen et al., 2025; Kim et al., 2025a; Cui et al., 2025). Specifically, Rafailov et al. (2023) show that the reward function r, which captures human preferences, can be approximated under the RLHF framework (Ouyang et al., 2022) as the log-likelihood ratio between the optimal (aligned) LLM policy π_r and a reference policy $\pi_{\texttt{ref}}$:

$$r(y) \approx \beta \cdot \log \frac{\pi_r(y)}{\pi_{\texttt{ref}}(y)}, \quad (4)$$

where β is a hyperparameter controlling the strength of KL regularization in RLHF.[3] This derivation of implicit reward enables reward modeling without an explicit reward model using only the relative likelihoods under two LLM policies, and yields a much more efficient preference learning algorithm, called DPO (see details in Appendix I).

In our setting, however, the personalized model $\pi_{\texttt{user}}$ is not trained with explicit KL regularization, as in standard RLHF. Nevertheless, we argue that the PEFT used for training $\pi_{\texttt{user}}$ implicitly imposes a similar constraint. For example, in LoRA (Hu et al., 2021), only the newly introduced low-rank matrices are updated, while the original model parameters remain fixed. This architectural constraint implicitly regularizes the updated model, preventing it from deviating significantly from the base model. As a result, the personalized model $\pi_{\texttt{user}}$ trained via PEFT remains close to the base model $\pi_{\texttt{base}}$, and the log-likelihood ratio between them can serve as a valid proxy for an implicit reward signal—namely, $r_{\texttt{user}}$. We further empirically validate that these log-likelihood ratios (Eq. 2) encode

[2]In this work, we only consider LoRA.

[3]While y is generated for input x, we omit this in Eq. 4 for the simplicity.

meaningful personalized signals through detailed analyses and results in Appendix D.

Interestingly, we note that this formulation, based on the ratio of log-likelihoods between two models, also appears in contrastive decoding (Li et al., 2023). In this sense, our insight reveals a novel connection between two popular decoding paradigms, contrastive decoding and reward-guided decoding. Following Li et al. (2023), we additionally introduce a hyperparameter α to control the strength of contrastive adjustment during decoding and further enhance personalization.

3.3 Aligning PEFT to user preference via DPO with synthetic negative response

While CoPE effectively maximizes the implicit user reward during decoding with the personalized model $\pi_{\texttt{user}}$, its performance can be further improved by explicitly aligning $\pi_{\texttt{user}}$ with the user's individual preferences during training.

One natural approach is to apply preference learning algorithms such as RLHF or DPO. However, a key practical challenge is a lack of negative examples ((*i.e.*, responses unlikely to come from the user) in the user dataset $H_{\texttt{user}}$. To address this, we propose a simple yet effective approach that synthesizes negative examples leveraging the implicit user reward $r_{\texttt{user}}$. Specifically, for each train query $x^i \in H_{\texttt{user}}$, we sample K candidate responses $\{\widetilde{y}^{i,1}, \dots, \widetilde{y}^{i,K}\}$ from the generic base model $\pi_{\texttt{base}}$. Among these, we select the response with the lowest implicit user reward, *i.e.*, the one that is most unlikely from the user:

$$\widetilde{y}^{i,*} = \arg \min_{y \in \{\widetilde{y}^{i,1}, \dots, \widetilde{y}^{i,K}\}} \sum_t r_{\texttt{user}}(y_t), \quad (5)$$

where the contrastive weight α is set to 1. Then, we construct a preference dataset $\mathcal{D}_{\text{pref}} := \{(x^i, y^i_{\texttt{pos}}, y^i_{\texttt{neg}})\}_{i=1}^N$ where $(x^i, y^i_{\texttt{pos}})$ from H_u, *i.e.*, $y^i_{\texttt{pos}} = y^i$, and $y^i_{\texttt{neg}} = \widetilde{y}^{i,*}$.

Using this preference dataset $\mathcal{D}_{\text{pref}}$, we further fine-tune $\pi_{\texttt{user}}$ with the following DPO loss:

$$\mathcal{L}_{\text{dpo}} = \mathop{\mathbb{E}}_{(x, y^{\text{pos}}, y^{\text{neg}}) \in \mathcal{D}_{\text{pref}}} \left[-\log \sigma \left(\beta \cdot r_{\text{dpo}} \right) \right], \quad (6)$$

where $r_{\text{dpo}} = r_{\texttt{user}}(y^{\text{pos}}) - r_{\texttt{user}}(y^{\text{neg}})$, and $\sigma(\cdot)$ denotes the sigmoid function. Optimizing this loss encourages the personalized model $\pi_{\texttt{user}}$ to assign higher reward to user-aligned responses compared to generic ones. This better modeling of implicit user reward further improves the effectiveness of reward-guided decoding through CoPE.

4 Experiments

In this section, we design our experiments to investigate the following questions:

- Does CoPE yield better personalization than existing baselines? (Table 1)
- Is CoPE applicable to models of varying architectures and parameter scales? (Table 2)
- How do different components in CoPE contribute to personalization performance? (Table 3)
- How sensitive is the performance of CoPE to different configuration settings? (Figure 3)

4.1 Setups

Datasets and metrics. We evaluate the effectiveness of CoPE primarily on personalized text generation tasks from the Large Language Model Personalization (LaMP) (Salemi et al., 2024) and LongLaMP (Kumar et al., 2024) benchmarks, which represent the most practical and impactful use cases of LLM personalization. In particular, we consider the following five tasks: News Headline Generation (LaMP 4), Scholarly Title Generation (LaMP 5), Abstract Generation (LongLaMP 2), Review Writing (LongLaMP 3), and Topic Writing (LongLaMP 4).[4] For evaluation, we mainly report ROUGE-1 and ROUGE-L scores across all tasks, which serve as standard evalaution metrics to measure the content relevance and structural similarity between the generated and ground-truth texts.

Baselines. We compare CoPE against several baselines to generate personalized responses from LLMs as follows: (1) *Base* – generation using a vanilla model without any supervised fine-tuning; (2) *RAG* (Lewis et al., 2021) – a retrieval-augmented generation method that directly injects user-related histories into the prompt without additional training; (3) *PAG* (Richardson et al., 2023) – a prompt-augmented generation approach that additionally incorporates user profiles to the prompt; (4) *TAM* (Tan et al., 2024) – generation with a task-adapted model trained on data from users excluding the test user, allowing familiarity with the task but lacking personalization; (5) *OPPU* (Tan et al., 2024) – generation with a personalized model equipped with user-specific adapters trained via simple supervised fine-tuning on user data.

[4] See behind rationale for this choice in Appendix A.

Table 1: **Main Results.** ROUGE-1 and ROUGE-L scores are reported for five tasks: Abstract Generation, Review Writing, and Topic Writing from LongLaMP; News Headline Generation and Scholarly Title Generation from LaMP. All experiments are conducted using `Mistral-7B-Instruct-v0.3`.

Methods	Abstract Generation		Review Writing		Topic Writing		News Headline		Scholarly Title	
	ROUGE-1	ROUGE-L	ROUGE-1	ROUGE-L	ROUGE-1	ROUGE-L	ROUGE-1	ROUGE-L	ROUGE-1	ROUGE-L
Base	0.341	0.186	0.287	0.126	0.246	0.105	0.119	0.105	0.409	0.324
RAG	0.347	0.205	0.272	0.128	0.243	0.115	0.141	0.124	0.425	0.347
PAG	0.344	0.186	0.256	0.125	0.262	0.107	0.118	0.102	0.372	0.289
TAM	0.357	0.204	0.289	0.122	0.253	0.107	0.200	0.179	0.514	0.456
OPPU	0.378	0.218	0.319	0.134	0.278	0.112	0.203	0.182	0.510	0.454
CoPE (Ours)	**0.392**	**0.239**	**0.335**	**0.146**	**0.281**	**0.120**	**0.205**	**0.184**	**0.519**	**0.461**

Implementation details. For methods that include a training step (TAM, OPPU, CoPE), all models are trained using AdamW (Loshchilov and Hutter, 2019) with a weight decay of 0.01. Linear learning rate decay was used with a warm-up ratio of 0.1. The batch size for the initial training of the task-adapted model is set to 8, while subsequent training stages use 4 to better capture the style of each user. Supervised training is conducted for 2 epochs with a learning rate of 1e-4 for LongLaMP and 1e-5 for LaMP. Subsequently, DPO training uses a 5e-6 learning rate for 1 epoch on LongLaMP and 2 epochs on LaMP. Also, we note that OPPU is continuously applied after TAM, following Tan et al. (2024). Similar to this, the proposed DPO step (Eq. 6) is applied after OPPU (see Figure 1).

All of the experiments are conducted using `Mistral-7B-Instruct-v0.3`,[5] except for those reported in Table 2. Greedy decoding is used to eliminate randomness, except for negative sample generation. In this case, we use `vLLM` (Kwon et al., 2023) with a temperature of 1.0 for faster decoding, generate $K = 3$ candidates using the task-adapted model, and select the final negative using the reward function (Eq. 5). For DPO training (Rafailov et al., 2023), we set coefficient for KL regularization $\beta = 3.0$ for LaMP tasks and $\beta = 0.05$ for LongLaMP tasks. At this point, we treat the task-adapted model as the base model $\pi_{\texttt{base}}$ and the DPO-trained model as the user model $\pi_{\texttt{user}}$ in Eq. 2. To implement the proposed reward-guided decoding (Eq. 3), we adopt the contrastive decoding (Li et al., 2023), with a plausibility threshold of $\tau = 0.1$ for both LaMP and LongLaMP tasks. The contrastive weight α is set to 0.3 for LaMP and 0.1 for LongLaMP tasks. We apply a repetition penalty of 1.0 for LaMP and 7.0 for LongLaMP, after observing that these values offered acceptable control over repetition in preliminary experiments.

[5] `https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3`

4.2 Main results

Table 1 summarizes the experimental results on five personalized open-ended text generation tasks. First, it is observed that the effectiveness of prompting-based methods is indeed limited. In particular, RAG and PAG exhibit limited improvement compared to training-based approaches, and even they are sometimes worse than the Base method, which does not apply any personalization technique. This observation validates the necessity for developing a training-based method like the proposed framework. Next, the experimental results in Table 1 also demonstrate that CoPE consistently outperforms all baseline methods across all tasks and metrics. For instance, CoPE achieves an average relative improvement of 10.57% in ROUGE-L compared to the task-adapted model, TAM. Notably, CoPE even outperforms a personalized model OPPU that relies solely on explicit user-specific fine-tuning, with average relative improvement of 5.67% in ROUGE-L. These results highlight the effectiveness of our framework, which maximizes implicit reward signals to better align with user preferences.

We further observe a task-specific trend across benchmarks. While RAG shows some effectiveness in LaMP tasks, its performance declines in the LongLaMP setting. For instance, RAG scores 5.23% lower than Base in Review Writing (ROUGE-1) and 1.22% lower in Topic Writing (ROUGE-1). This highlights the increased difficulty of LongLaMP tasks, where simple retrieval of user history is no longer sufficient. In contrast, CoPE remains effective even in this more demanding setting. In fact, CoPE demonstrates a significantly higher relative improvement in the

Table 2: **Compatibility of CoPE.** ROUGE-L scores on the Abstract Generation task across different LLMs.

Methods	LLaMA 3.1-8B	Gemma 3-4B	Qwen 2.5-1.5B
Base	0.172	0.135	0.130
RAG	0.183	0.170	0.128
PAG	0.183	0.169	0.130
TAM	0.198	0.181	0.150
OPPU	0.202	0.194	0.163
CoPE (Ours)	**0.261**	**0.237**	**0.233**

Table 3: **Ablation study.** The effects of contrastive decoding (CD) and direct preference optimization (DPO).

	CD	DPO	Abstract Generation		News Headline	
			ROUGE-1	ROUGE-L	ROUGE-1	ROUGE-L
OPPU	✗	✗	0.378	0.218	0.203	0.181
	✓	✗	0.385	0.232	0.204	0.183
	✗	✓	0.386	0.230	0.203	0.182
CoPE (Ours)	✓	✓	0.392	0.239	0.205	0.184

more challenging LongLaMP setting—achieving a 16.33% gain in ROUGE-L over the task-adapted model, compared to just 1.95% in LaMP. This suggests that LongLaMP tasks may offer greater room for personalization gains when properly modeled and carefully optimized. We also note that the tasks in LongLaMP tend to involve more subjective or user-specific expression, making them especially well-suited for personalized generation when guided by an effective framework like CoPE.

4.3 Additional analyses

Here, we provide additional analyses of CoPE with the experiments on Abstract Generation from LongLaMP and News Headline Generation from LaMP. More analyses are in Appendix C.

Generalization to various LLMs. In this section, we explore the applicability of CoPE to various LLMs and sizes. Results are presented in Table 2. The experimental results validate that CoPE generalizes well across a diverse range of LLMs, including LLaMA-3.1-8B-Instruct (Grattafiori et al., 2024), Gemma-3-4B-it (Team et al., 2025), and Qwen2.5-1.5B-Instruct (Qwen et al., 2025). Compared to TAM, CoPE significantly improves ROUGE-L by 31.8% on LLaMA-3.1-8B , 30.9% on Gemma-3-4B-it, and 55.3% on Qwen2.5-1.5B. Similarly, compared to OPPU, CoPE achieves a relative improvement of 29.2% on LLaMA-3.1-8B, 22.2% on Gemma-3-4B-it, and 42.9% on Qwen2.5-1.5B. These consistent improvements suggest that CoPE does not simply rely on a specific environment setting. Instead, our framework is generalizable and flexible with respect to model architecture and parameter scale. This makes CoPE a broadly applicable framework for deployment across diverse LLMs.

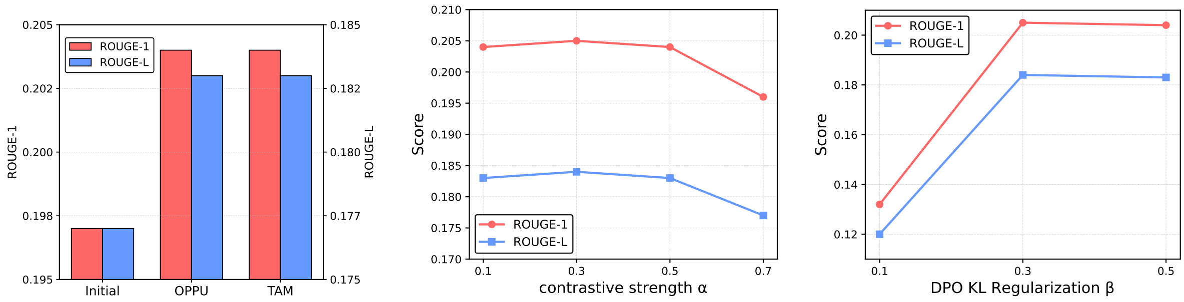
Ablation study. We now proceed to validate the individual components of CoPE. To assess the contribution of each component to overall performance of CoPE, we perform a detailed ablation study.

For this analysis, we primarily conducted experiments on Abstract Generation and News Headline Generation tasks, serving as representative tasks for LongLaMP and LaMP, respectively. The results are presented in Table 3. Here, it is observed that adding each component progressively improves the performance. Comparing with the OPPU baseline, applying only contrastive decoding increases the scores in both tasks, as it encourages the model to generate outputs that are more distinguishable from less preferred candidates. Meanwhile, in the training side, introducing only preference-aligned training also improves the performance of the model, as it guides the model to internalize user preferences by learning to favor higher-quality responses over inferior ones during fine-tuning.

Finally, when combining these components to formulate an implicit reward maximization objective both during training and decoding, we observe the highest performance. These results indicate that each component independently contributes to performance improvements, and their integration yields the most substantial gains across tasks. This is because both components work synergistically to align model outputs with implicit user preferences: training encourages the model to internalize preference signals through comparisons between better and worse responses, while decoding promotes outputs that more closely reflect these learned preferences at inference time. Together, they implicitly guide the model to maximize a user-aligned reward signal, even in the absence of explicit supervision from an external model.

Sensitivity of CoPE. Figure 3 presents a sensitivity analysis of key components in the proposed framework. In this section, we conduct experiments on the News Headline Generation task, chosen for its shorter runtime, to explore the behavior of CoPE under different settings.

We begin by examining the choice of base model for contrastive decoding (*i.e.*, $\pi_{\texttt{base}}$ to calculate likelihood for the denominator in Eq. 2). We first note that TAM is originally used as the base model



(a) Choice of base model $\pi_{\texttt{base}}$ (b) Contrasting strength α (c) DPO KL regularization β

Figure 3: **Different hyperparameters.** (a) Performance variation by base model choice. (b) Effect of contrastive strength α. (c) Effect of KL regularization β in DPO. ROUGE-1 and ROUGE-L scores are reported.

News Headline Example 1	
Query	Generate a headline for the following article: When we first saw Michael H. Rohde's photography series "Below The Floor" on Design-Milk.com, we were floored. (Pun intended)
User Answer	Michael H. Rohde, German Photographer, Shoots Breathtaking Series 'Below The Floor' (PHOTOS)
TAM	Craft Of The Day: Create A Floating Photo Gallery With This DIY
OPPU	'Below The Floor' Photography Series Reveals The Hidden Beauty In The Places We Walk On
CoPe (ours)	'Below The Floor' Photography Series By Michael H. Rohde Is A Whole New Perspective On The World (PHOTOS)

News Headline Example 2	
Query	Generate a headline for the following article: Frances McDormand memorably called for inclusion riders in her Oscars acceptance speech.
User Answer	Michael B. Jordan Says His Company Will Adopt Inclusion Rider On All Projects
TAM	'The Big Sick' And 'Get Out' Join The Movement For Equal Representation In Hollywood
OPPU	'Inclusion Rider' Is The Powerful New Tool That Could Change Hollywood
CoPe (ours)	'The Shape Of Water' Producer Says He'll Use Inclusion Rider On All Future Projects

Figure 4: **A qualitative example of CoPe on the News Headline Generation task (LaMP 4).** The output of CoPe contains more words that align with the user gold response compared to TAM and OPPU. Words overlapping with the user's answer are highlighted, and tokens that CoPe uniquely emphasizes for personalization, which are not captured by other baselines, are **boxed**. More qualitative examples from other tasks are provided in Appendix L.

in CoPe, as it yields better understanding of the target task. To investigate this, we performed experiments by varying the base models from TAM to init (*i.e.*, initial Mistral model) and OPPU (*i.e.*, after adaption to user and before DPO). The results are presented in Figure 3(a), and one can verify that the current design choice is the best and using init is the worst. The findings suggest that using either OPPU or TAM as the base model yields the best performance. We hypothesize that these models help isolate and downweigh non-personalized features, allowing user-specific characteristics to be more prominently reflected.

Next, we analyze the sensitivity of CoPe to two key hyperparameters: the contrastive strength (α) and the KL regularization coefficient (β) in preference-aligned training. These two hyperparameters are crucial in the decoding and training components of our framework, respectively. Figure 3(b) shows the effect of varying the contrastive strength α under fixed $\beta = 3.0$. We observe that CoPe performs reliably across a range of α values, with a slight peak around $\alpha = 0.3$. While stronger contrastive signals may lead to marginal decreases in output quality, the overall performance remains consistently stable, which demonstrates the robustness of CoPe to decoding-time variations.

Figure 3(c) illustrates the impact of varying the KL regularization coefficient β during training. As β increases from 0.1 to 0.3, both ROUGE-1 and ROUGE-L scores improve, after which performance growth starts to hinder. This suggests that CoPe benefits from moderate regularization while remaining resilient to further increases. These results indicate that CoPE performs consistently well across a range of configurations, underscoring its robustness and reliability without signs of overfitting to specific hyperparameter values.

5 Conclusion

In this work, we propose CoPE, the first decoding-based framework for personalizing LLMs. Specifically, CoPE is a reward-guided decoding approach that maximizes implicit rewards of each user, thereby enhancing personalization without requiring external reward models. Our comprehensive experiments show that CoPE consistently outperforms various baselines across multiple tasks and also is well-generalized to various types and scales of LLMs. Consequently, these results demonstrate that it is not only effective but also a practical framework for decoding-time personalization.

Limitations

While CoPE shows consistent improvements in personalized generation, it uses a fixed set of hyperparameters (*e.g.*, learning rate, batch size, LoRA rank) for all users, regardless of dataset size or characteristics. This uniform setting may be suboptimal when data varies in volume or domain.Future work should explore adaptive strategies that adjust hyperparameters to user-specific profiles. In addition, we focus only on LoRA as the PEFT method, but different PEFT approaches (Li and Liang, 2021; Liu et al., 2022) are also considerable. Since our approach does not depend on a particular method and most PEFT variants share architectural constraints with LoRA, we expect that CoPE is also easily deployed for these approaches.

Ethics Statement

We investigate LLM adaptation to individual users using PEFT methods such as LoRA. To ensure user privacy, our approach neither stores nor exposes raw user data and updates only a small set of task- and user-specific parameters. In addition, all negative samples for preference optimization are synthetically generated from a base model, rather than extracted from real user outputs. Although we do not explicitly assess membership inference risks, the use of PEFT and synthetic negatives may provide stronger privacy protection than full-model fine-tuning. All datasets and models used in this study are publicly available and used in line with their designated purposes. An AI assistant (ChatGPT) was used to refine the manuscript writing.

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A Datasets

For the experiments, we focus mainly on the text generation tasks provided in the LaMP (Salemi et al., 2024) and LongLaMP (Kumar et al., 2024) benchmarks. Following these benchmarks, we use ROUGE-1 and ROUGE-L as metrics for evaluation. Detailed descriptions of each task are as follows.

LaMP 4: News Headline Generation. This task evaluates the ability of a model to automatically generate headlines for given news articles, conditioned on an author profile containing historical article-title pairs, thereby capturing distinctive stylistic patterns in journalistic writing.

LaMP 5: Scholarly Title Generation. This task assesses the capacity of a model to generate appropriate titles for scholarly article abstracts conditioned on an author profile of historical article-title pairs, reflecting distinct academic writing style.

LongLaMP 2: Abstract Generation. This task focuses on evaluating the proficiency of a model in generating scientific abstracts given paper titles and keywords by leveraging an author profile of previous publications to emulate characteristic academic writing style and domain-specific terminology

LongLaMP 3: Review Writing. This task tests the ability of a model to automatically generate comprehensive product reviews based on product specifications and user experiences, conditioned on a user profile of review history to reflect distinctive evaluative style and subjective perspective.

LongLaMP 4: Topic Writing. This task evaluates the capability of a model to generate Reddit post content based on post summaries while maintaining the unique writing style of individual users, requiring the generation of content from a given summary conditioned on a user profile containing their historical Reddit posts.

In LaMP, we only consider News Headline Generation (LaMP 4) and Scholarly Title Generation (LaMP 5) as they are only applicable generation tasks with proper labels; Citation Identification (LaMP 1), Movie Tagging (LaMP 2), and Product Rating (LaMP 3) are discriminative, while Email Subject Generation (LaMP 6) and Tweet Paraphrasing (LaMP 7) lack gold labels, so none of these are included. For LongLaMP, we only considered Abstract Generation (LongLaMP 2), Review Writing (LongLaMP 3), and Topic Writing (LongLaMP 3) because Email Completion (LongLaMP 1) relies on the Avocado Research Email Collection, a private dataset with restricted access. Overall, our task selection focuses on (1) accessible and (2) evaluable (3) text-generation tasks for assessing LLM personalization. Throughout our framework, we follow the setup of an earlier work (Tan et al., 2024): we use 100 users with the longest activity histories as the test set, and the remaining users to train the task-adapted base model.

B Baselines Details

Detailed explanations for each baseline are provided below. Black boxes indicate vanilla models and prompt-base baselines (*i.e.*, training-free), while white boxes represent training-base ones.

- ■ **Base model** refers to the generation with the original LLM without any task-specific fine-tuning or additional conditioning. It represents the vanilla, commonly used standard pre-trained model as released.

- ■ **RAG: Retrieval-Augmented Generation** (Lewis et al., 2021) is a method that retrieves user-related history records and directly incorporates them into the prompt. Following the setup in LaMP (Salemi et al., 2024), we retrieve the top-k history records for each user. In our experiments, we set $k = 3$, meaning the three most relevant records are selected using BM25 (Robertson and Walker, 1994)—a standard keyword-based retrieval method. We implement BM25 using the `rank_bm25` library with `BM25Okapi`.

- ■ **PAG: Profile-Augmented Generation** (Richardson et al., 2023) is a technique for personalizing LLM outputs by conditioning on structured user profiles. Following the prior work (Tan et al., 2024), we generate user profiles using the `vicuna-7B` model (Chiang et al., 2023), based on the past responses of a typical user. Each profile captures key stylistic characteristics, such as tone, lexical choices, and recurring templates. The model then uses these profiles as a guide to generate output that aligns closely with the user style.

- ❑ **TAM: Task Adapted Model** (Tan et al., 2024) is trained on data from users other than the selected 100 test users. The objective of this model is to adapt the base model to the task

Table 4: **Dataset statistics.** Base LLM training corresponds to *TAM*, and Personal PEFT training to OPPU.

Task	Base LLM Training (TAM)			Personal PEFT Training (OPPU)		
	#Train	L_{in}	L_{out}	#Profile	L_{in}	L_{out}
Abstract Generation	31,808	70.4 ± 13.3	233.1 ± 117.5	1,296.7 ± 446.4	604.4 ± 142.7	210.5 ± 92.8
Review Writing	19,649	185.1 ± 109.0	407.2 ± 299.5	759.3 ± 324.2	1,143.0 ± 343.3	511.8 ± 294.2
Topic Writing	21,119	56.6 ± 54.8	358.3 ± 316.9	260.6 ± 314.0	759.8 ± 321.8	358.3 ± 255.4
News Headline Generation	7,275	53.6 ± 19.0	15.5 ± 6.0	270.1 ± 182.1	92.2 ± 11.3	18.6 ± 5.2
Scholarly Title Generation	16,076	230.6 ± 97.9	17.9 ± 6.1	444.0 ± 121.6	266.4 ± 85.9	16.4 ± 5.8

Table 5: **Compatibility of CoPe.** ROUGE-1 scores on the Abstract Generation task across different LLMs.

Methods	LLaMA 3.1-8B	Gemma 3-4B	Qwen 2.5-1.5B
Base	0.340	0.270	0.278
RAG	0.330	0.295	0.240
PAG	0.333	0.292	0.241
TAM	0.355	0.326	0.298
OPPU	0.363	0.347	0.304
CoPe (Ours)	**0.417**	**0.393**	**0.384**

in a general manner via LoRA (Low-Rank Adaptation) (Hu et al., 2021), enabling it to understand the task setup without being exposed to the specific styles of the target users.

- **OPPU: One PEFT Per User Model** (Tan et al., 2024) is a baseline that fine-tunes the LoRA adapter from the TAM model on individual users. Specifically, the historical data of each user is used to fine-tune the LoRA adapter from the TAM model, resulting in 100 separate personalized adapters. Intuitively, each LoRA adapter is specialized to learn the unique style of a specific user.

C More Quantitative Results

In this section, we provide more quantitative results. In Table 5, we present the results under various LLMs on Abstract Generation using ROUGE-1, instead of ROUGE-L in Table 2. One can verify that CoPe significantly improve ROUGE-1 as well. Next, in Tables 6 and 7, we present the results on News Headline Generation using ROUGE-1 and ROUGE-L scores, respectively. Here, it is observed that the proposed CoPe is continuously effective.

D Empirical Validation of Log-Likelihood Ratios as Implicit Rewards

To empirically validate our use of log-likelihood ratios as implicit reward signals, we conducted an analysis comparing scores produced by user-specific models and those produced by models trained on other users. For example, given user 1, we compute the log-likelihood ratio score (Eq. 2). on user 1's training samples using two models: (1) the OPPU model of user 1 (`score_user`), and (2) OPPU models trained on all other users (`score_others`). Our core intention with this validation is to demonstrate that the log-likelihood ratio with personalized model meaningfully captures user-specific signals. In other words, if it truly reflects personalization, then a model fine-tuned for a given user should consistently assign higher scores to that user's own data than models fine-tuned for different users. To ensure robustness, we repeated this comparison across 10 randomly selected users. For each user, we evaluated the scores on a randomly sampled 20% subset of their profile history. The results are presented in Table 8.

By comparing `score_user` and `score_others` across users and averaging over profile data, we find that each user's model assigns higher scores to their own data. This shows that log-likelihood ratios capture personalized signals, supporting their use as an implicit reward approximator.

Table 6: **Compatibility of CoPe.** ROUGE-1 scores on the News Headline Generation task across different LLMs.

Methods	LLaMA 3.1-8B	Gemma 3-4B	Qwen 2.5-1.5B
Base	0.127	0.070	0.117
RAG	0.146	0.098	0.136
PAG	0.129	0.099	0.128
TAM	0.188	0.161	0.142
OPPU	0.191	0.164	0.143
CoPe (Ours)	**0.211**	**0.168**	**0.147**

Table 7: **Compatibility of CoPe.** ROUGE-L scores on the News Headline Generation task across different LLMs.

Methods	LLaMA 3.1-8B	Gemma 3-4B	Qwen 2.5-1.5B
Base	0.110	0.063	0.104
RAG	0.129	0.089	0.121
PAG	0.112	0.089	0.114
TAM	0.169	0.144	0.127
OPPU	0.171	0.147	0.127
CoPe (Ours)	**0.190**	**0.151**	**0.131**

Table 8: **Validation of implicit reward approximation.** Comparison of log-likelihood ratio scores from user-specific models (`score_user`) and models trained on other users (`score_others`).

User Index	User Own (score_user)	Other 9 Users Avg (score_others)
3	0.087	0.025
13	0.096	0.028
14	0.131	0.023
17	0.083	0.023
28	0.097	0.029
31	0.090	0.026
35	0.082	0.025
81	0.099	0.030
86	0.088	0.025
94	0.093	0.026
Avg	**0.095**	**0.026**

Table 9: **Ablation study.** The effects of contrastive decoding (CD) and direct preference optimization (DPO). R-1 and R-L represents Rouge-1 and Rouge-L scores respectively.

	CD	DPO	Abstract Gen.		Review Writing		Topic Writing	
			R-1	R-L	R-1	R-L	R-1	R-L
OPPU	✗	✗	0.378	0.218	0.319	0.134	0.278	0.112
	✓	✗	0.385	0.232	**0.335**	0.145	**0.285**	**0.122**
	✗	✓	0.386	0.230	0.323	0.138	0.280	0.114
CoPe (Ours)	✓	✓	**0.392**	**0.239**	**0.335**	**0.146**	0.281	0.120

	CD	DPO	News Headline		Scholarly Title		Average	
			R-1	R-L	R-1	R-L	R-1	R-L
OPPU	✗	✗	0.203	0.181	0.510	0.454	0.338	0.220
	✓	✗	0.204	0.183	0.514	0.456	0.345	0.227
	✗	✓	0.203	0.182	0.517	0.457	0.342	0.224
CoPe (Ours)	✓	✓	**0.205**	**0.184**	**0.519**	**0.461**	**0.346**	**0.230**

E Extended Ablation Experiments

A full ablation table covering all tasks is presented in Table 9. Overall, our proposed framework CoPe continues to show a clear trend of performance improvement upon each component (CD and DPO).

On average across tasks, DPO improved ROUGE-1 and ROUGE-L by 1.09% and 2.3%, while CD yielded higher gains (2.13% ROUGE-1, 5.02% ROUGE-L). Their combination achieved the best performance, with 2.51% and 5.79% increases over OPPU. Although a few tasks (e.g., Topic Writing) showed weaker results under both methods, likely due to universal hyperparameters being suboptimal, the overall trend supports their combined effectiveness.

F Perplexity and Fluency Analysis

A common concern with decode-time manipulation methods such as contrastive decoding (CD) is whether they degrade fluency or coherence of the generated text. In this section, we explore the relationship between perplexity, our ratio-based reward proxy, and overall personalization quality.

Perplexity measures how well a reference model predicts a sequence in absolute terms. In contrast, the user/base probability ratio (Eq. 2) we employ is a relative measure that captures shifts in predicted token probabilities between a user-specific model and the base model. This relative shift serves as the personalization signal in our framework. Thus, while perplexity is informative about fluency under a particular reference model, it is not directly comparable to the ratio we use as implicit reward.

To empirically assess whether CD harms fluency, we measured the perplexity of all methods' outputs using the same reference LM (`Mistral-7B-Instruct-v0.3`). Results are summarized in Table 10. CD does not increase perplexity by more than $\pm$2.4 points compared to the base OPPU_SFT, and in fact achieves the lowest perplexity on three of the five tasks (e.g., 7.01 vs. 12.34 on Abstract Generation). Additionally, standard deviations are small, which indicates stable behavior.

Furthermore, we also observe that human gold texts show higher perplexity than model outputs. This phenomenon is a natural outcome in personalization settings, as authentic user texts often include creative, informal, and unusual elements that are harder for a reference LM to predict.

Analytically, in Figure 5 the gold text contains spelling variations ("washigngton", "feild") ans colloquial phrases ("So yah, cool"), which raise perplexity under a reference LM, but this does not undermine our ratio-based reward, which relies on relative shifts between user-specific and base models rather than the absolute perplexity value itself.

G Robustness to User Heterogeneity

While evaluating based on average performance across users is widely adopted, one may be concerned that the result can be over-estimated by few outlier users. Therefore, to test the robustness of CoPe under such heterogeneous user conditions, we compared it with TAM and the OPPU baseline at the instance level. Specifically, we measure how many instances are improved by our method compared to the baselines.

Table 10: **Perplexity analysis.** Mean and standard deviation (std) of perplexity measured with Mistral-7B-Instruct-v0.3 as the reference LM.

Task	Metric	Gold Data	TAM	OPPU	OPPU+CD	OPPU+DPO	COPE
Abstract Generation	mean	214.43	13.27	12.34	7.01	13.00	15.91
	std	396.39	10.11	14.75	2.91	12.12	21.91
Topic Writing	mean	363.10	26.32	13.41	16.86	15.80	17.79
	std	439.49	21.40	11.30	20.12	15.13	20.21
Review Writing	mean	780.07	17.13	20.69	15.78	20.86	19.01
	std	1233.23	11.28	18.47	12.73	15.26	13.90
News Headline	mean	41.79	28.71	25.86	28.25	27.20	27.32
	std	26.30	30.34	17.26	19.09	17.81	17.88
Scholarly Title	mean	79.79	55.65	47.37	47.37	67.27	70.48
	std	64.57	40.29	30.72	30.72	49.52	54.24

Gold	It is legalin washignton state to pay feild workers less then minimum wage provided you give them basic shelter. ... So yah, cool. And as to your 'we can't make everyone a citizin' ...
Generated	It is not as simple as 'just' doing this or that, and there are many reasons why people don't want to go into politics...

Figure 5: **Example illustrating perplexity differences between gold and generated text.** A user's gold text often contains spelling variations, colloquial expressions, and conversational truncations, which are harder for a reference LM to predict, resulting in higher perplexity. In contrast, model-generated text tends to be more regular and thus achieves lower perplexity.

As shown in Table 11, COPE outperformed TAM on 56%–80% of instances, while OPPU improved on only about 50-69%. Although this analysis is conducted at the instance level, it provides strong evidence that even under a fixed hyper-parameter setting, COPE generalizes robustly across heterogeneous writing styles, domains, and data sizes. We leave exploring efficient, light-weight user-specific hyper-parameter adaptation as promising future work to pursue.

H Statistical Reliability of Results

To assess the reliability and significance of the reported performance, we quantify the variability of ROUGE scores by measuring the standard error (SE) across test samples. Table 12 shows the averaged results across datasets. Both ROUGE-1 and ROUGE-L exhibit very small SE values (below ≈ 0.009), corresponding to only 2–3% of the mean score and yielding a 95% confidence interval within ± 0.02 ROUGE points. This indicates that the observed improvements are unlikely to be due to random variation in the evaluation set.

In addition, to complement mean/SE figures with an instance-level view, we compute the percentage of test instances (IDs) where a model's ROUGE score matches or exceeds TAM. As shown in Table 13, COPE surpasses TAM on 66.77% of instances for ROUGE-1 and 71.55% for ROUGE-L, about 8 and 12 points above OPPU. Overall, the low SE values and high win-or-tie rates show that COPE's gains are statistically reliable and consistently realized at the instance level.

I Background for RLHF and DPO

Let us denote LLM as π_θ, which generates an output sequence (*e.g.*, response) y for a given input sequence (*e.g.*, prompt) x, *i.e.*, $y \sim \pi_\theta(\cdot|x)$. Then, the goal of LLM alignment is to make π_θ provide human-aligned responses to various input prompts. To this end, let assume that the preference dataset $\mathcal{D} = \{(x, y_l, y_w)\}$ is available which consists of the triplets of input prompt x, preferred response y_w, and dispreferred response y_l. Here, the preference labels were annotated by a ground truth annotator, that is usually a human expert.

Table 11: **Instance-level robustness comparison.** "R-1 Improved (%)" and "R-L Improved (%)" denote the percentage of test instances for which the model outperforms TAM. The **Average** row reports a *macro-average across the five tasks* (unweighted by instance counts); hence Total Instances is not applicable.

Task	Model	CD	DPO	R-1 Improved (%)	R-L Improved (%)	Total Instances
Abstract Generation	OPPU	✗	✗	50.35	52.45	143
	+ CD	✓	✗	58.04	65.03	
	+ DPO	✗	✓	56.64	66.43	
	CoPE (ours)	✓	✓	**63.64**	**76.22**	
Review Writing	OPPU	✗	✗	69.33	68.10	163
	+ CD	✓	✗	75.46	75.46	
	+ DPO	✗	✓	68.10	72.39	
	CoPE (ours)	✓	✓	**77.91**	**81.60**	
Topic Writing	OPPU	✗	✗	58.33	60.61	132
	+ CD	✓	✗	56.06	65.15	
	+ DPO	✗	✓	**59.09**	55.30	
	CoPE (ours)	✓	✓	56.06	**65.91**	
News Headline	OPPU	✗	✗	61.01	60.86	6725
	+ CD	✓	✗	56.85	57.71	
	+ DPO	✗	✓	61.32	61.56	
	CoPE (ours)	✓	✓	**79.61**	**80.24**	
Scholarly Title	OPPU	✗	✗	52.83	53.77	106
	+ CD	✓	✗	52.83	53.77	
	+ DPO	✗	✓	**65.09**	**66.98**	
	CoPE (ours)	✓	✓	56.60	53.77	
Average	OPPU	✗	✗	58.37	59.16	-
	+ CD	✓	✗	59.85	63.43	
	+ DPO	✗	✓	62.05	64.53	
	CoPE (ours)	✓	✓	**66.77**	**71.55**	

Table 12: **Mean ROUGE and standard error (SE) across test samples.** SE values remain consistently small (< 0.009), indicating stable results.

Model	Mean R-1 ↑	Mean R-L ↑	SE R-1 ↓	SE R-L ↓
TAM	0.323	0.214	0.008	0.007
OPPU	0.338	0.220	0.009	0.007
CoPE (ours)	**0.346**	**0.228**	0.009	0.007

Table 13: **Instance-level win rates against TAM.** Values denote the percentage of test instances where a model's ROUGE is equal to or higher than TAM.

Model	R-1 ↑	R-L ↑
OPPU	58.37	59.16
CoPE (ours)	**66.77**	**71.55**

Reward modeling and RL fine-tuning. Since a pairwise preference between y_w and y_l is hard to model directly, one of the common practices is introducing reward function $r(x, y)$ and modeling the preference based on this using the Bradley-Terry model (Bradley and Terry, 1952):

$$p(y_w \succ y_l \mid x) = \frac{\exp(r(x, y_w))}{\exp(r(x, y_w)) + \exp(r(x, y_l))}.$$

From this, one can introduce a parametrized reward model $r_\phi(x, y)$ by estimating its parameters with the maximum-likelihood objective:

$$\mathcal{L}_r = \mathop{\mathbb{E}}_{(x, y_w, y_l) \sim \mathcal{D}} \left[-\log \sigma \left(r_\phi(x, y_w) - r_\phi(x, y_l) \right) \right],$$

where σ is a sigmoid function. After this reward modeling procedure, one could improve the alignment of LLM π_θ by optimizing it to maximize the reward from r_ϕ. Here, KL-distance from the reference model π_{ref} is incorporated as a regularization to prevent the reward over-optimization of π_θ, with a hyper-parameter $\beta > 0$ (Ouyang et al., 2022):[6]

$$\mathcal{L}_{\text{RLHF}} = -\mathbb{E}_{y \sim \pi_\theta, x \sim \rho} \left[r_\phi(x, y) \right] + \beta D_{\text{KL}} \left(\pi_\theta(y|x) \| \pi_{\text{ref}}(y|x) \right).$$

[6] π_{ref} is usually initialized with supervised fine-tuned (SFT) LLM. Also, π_θ is initialized with π_{ref}.

Direct preference optimization. Rafailov et al. (2023) propose an alternative approach to align LLM π_θ with the preference dataset $\mathcal{D}$, which is called Direct Preference Optimization (DPO). DPO integrates a two-step alignment procedure with reward modeling and RL fine-tuning into a single unified fine-tuning procedure. Specifically, the optimal reward function is derived from the RLHF objective, with the target LLM π_θ and the reference model π_{ref}, which is often called implicit reward:

$$r(x, y) = \beta \log \frac{\pi_\theta(y \mid x)}{\pi_{\text{ref}}(y \mid x)} + \beta \log Z(x),$$

where $Z(x) = \sum_y \pi_{\text{ref}}(y \mid x) \exp\left(\frac{1}{\beta} r(x, y)\right)$. Then, the preference between two responses could be measured using this reward derivation, and π_θ is optimized to maximize this preference of y_w over y_l using the preference dataset $\mathcal{D}$.

$$p_\theta(y_w \succ y_l \mid x) = \sigma\Bigg(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{\text{ref}}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{\text{ref}}(y_l \mid x)}\Bigg),$$

$$\mathcal{L}_{\text{DPO}} = \mathbb{E}_{(x, y_w, y_l) \sim \mathcal{D}} \left[- \log p_\theta(y_w \succ y_l | x)\right].$$

J Prompts

Below are prompts used in our experiments. Note that the text in {BRACES} is a placeholder for user- and query-specific input.

News Headline Generation

You are a news headline generator.
Generate a headline for the following article.
article: {ARTICLE}
headline:

Scholarly Title Generation

You are a scholarly title generator.
Generate a title for the following abstract of a paper. abstract: {ABSTRACT}
title:

Abstract Generation

You are an abstract writer.
Generate the review text written by a reviewer who has a given an overall rating of "{RATING}*" for a product with description "*{PRODUCT}*". The summary of the review text is "*{SUMMARY}*".*
Review:

Review Writing

You are a review writer.
Generate an abstract for the title "{TITLE}*".*
Abstract:

Topic Writing

You are a creative content generator for Reddit posts.
Generate the content for a reddit post.
post: {POST}
content:

K Chat Templates

In this section, we provide the chat templates we applied for experiments. We also include the chat templates of other LLMs used to test the generalization of CoPe.

Mistral-7B-Instruct-v0.3

```
MISTRAL_CHAT_TEMPLATE = """
{% if messages[0]['role'] == 'system' %}
{% set loop_messages = messages[1:] %}
{% set system_message = messages[0]['content'].
    strip() + '\n' %}
{% else %}
{% set loop_messages = messages %}
{% set system_message = '' %}
{% endif %}
{% for message in loop_messages %}
    {% if loop.index0 == 0 %}
        {% set content = system_message + message
            ['content'] %}
    {% else %}
        {% set content = message['content'] %}
    {% endif %}
    {% if message['role'] == 'user' %}
        {{ '[INST] ' + content.strip() + ' [/INST
            ]' }}
    {% elif message['role'] == 'assistant' %}
        {{ ' ' + content.strip() + ' ' +
            eos_token }}
    {% endif %}
{% endfor %}
"""
```

LLaMA-3.1-8B-Instruct

```
LLAMA_CHAT_TEMPLATE = """
 {{- bos_token }}
 {%- if messages[0]['role'] == 'system' %}
     {%- set system_message = messages[0]['
         content'].strip() %}
     {%- set loop_messages = messages[1:] %}
     {{- '<|start_header_id|>system<|
         end_header_id|>\\n\\n' + system_message
          + '<|eot_id|>' }}
 {%- else %}
     {%- set loop_messages = messages %}
 {%- endif %}
 {%- for message in loop_messages %}
     {%- if message['role'] == 'user' %}
         {{- '<|start_header_id|>user<|
             end_header_id|>\\n\\n' + message['
             content'].strip() + '<|eot_id|>' }}
     {%- elif message['role'] == 'assistant' %}
         {{- '<|start_header_id|>assistant<|
             end_header_id|>\\n\\n' + message['
             content'].strip() + '<|eot_id|>' }}
```

```
    {%- endif %}
 {%- endfor %}
 {%- if add_generation_prompt %}
    {{- '<|start_header_id|>assistant<|
         end_header_id|>\\n\\n' }}
 {%- endif %}"""
```

GEMMA-3-4B-it

```
GEMMA_CHAT_TEMPLATE = """
"{% set bos_token = '<bos>' %}
{% set eos_token = '<eos>' %}

{{ bos_token }}
{% if messages[0]['role'] == 'system' %}
  {{ 'System: ' + messages[0]['content'].strip()
       + '\n' }}
  {% set loop_messages = messages[1:] %}
{% else %}
  {% set loop_messages = messages %}
{% endif %}

{% for message in loop_messages %}
  {% if message['role'] == 'user' %}
    {{ 'User: ' + message['content'].strip() + '\
        n' }}
  {% elif message['role'] == 'assistant' %}
    {{ 'Assistant: ' + message['content'].strip()
         + eos_token + '\n' }}
  {% endif %}
{% endfor %}
{{ 'Assistant:' }}"
"""
```

Qwen2.5-1.5B-Instruct

```
QWEN_CHAT_TEMPLATE = ''' {%- if messages[0]['
    role'] == 'system' %}
    {{- '<|im_start|>system\\n' + messages[0]['
         content'].strip() + '<|im_end|>\\n' }}
    {%- set loop_messages = messages[1:] %}
 {%- else %}
    {%- set loop_messages = messages %}
 {%- endif %}
 {%- for message in loop_messages %}
    {%- if message['role'] == 'user' %}
        {{- '<|im_start|>user\\n' + message['
             content'].strip() + '<|im_end|>\\n'
             }}
    {%- elif message['role'] == 'assistant' %}
        {{- '<|im_start|>assistant\\n' + message
             ['content'].strip() + '<|im_end|>\\n
             ' }}
    {%- endif %}
 {%- endfor %}
 {%- if add_generation_prompt %}
    {{- '<|im_start|>assistant\\n' }}
 {%- endif %}
'''
```

L More Qualitative Examples

In this section, we present the additional qualitative examples similar to Figure 4. Figures 6, 7, 8, and 9 clearly show the advantages of COPE, compared to the baseline methods.

Scholarly Title	
Query	Generate a title for the following abstract of a paper: Despite advances in multicore smartphone technologies, battery consumption still remains one of customer's least satisfying features. This is because existing energy saving techniques do not consider the electrochemical characteristics of batteries, which causes battery consumption to vary unpredictably, both within and across applications. Additionally, these techniques provide application specific fixed performance degradation in order to reduce energy consumption. Having a performance penalty, even when a battery is fully charged, adds to customer dissatisfaction. We propose a control-based approach for runtime power management of multicore smartphones, which scales the frequency of processing cores in response to the battery consumption, taking into account the electrochemical characteristics of a battery. The objective is to enable graceful performance modulation, which adapts with application and battery availability in a predictable manner, improving quality-of-user-experience. Our control approach is practically demonstrated on embedded Linux running on Cortex A15-based smartphone development platform from nvidia. A thorough validation with mobile and Java workloads demonstrate 2.9\u00d7 improvement in battery availability compared to state-of-the-art approaches.
User Answer	Graceful Performance Adaption through Hardware-Software Interaction for Autonomous Battery Management of Multicore Smartphones
TAM	Predictable Quality-of-User-Experience Management for Multicore Smartphones.
OPPU	Predictable performance management for multicore smartphones
CoPe (ours)	Predictable Performance Management for Battery-Powered Multicore Smartphones

Figure 6: **Qualitative example for Scholarly Title Generation**

Abstract Generation	
Query	Generate an abstract for the title \"A resolved CFD-DEM coupling model for modeling two-phase fluids interaction with irregularly shaped particles\" using the following items: 1. Resolved coupling model\n2. Multi-sphere clumps\n3. Benchmark cases\n4. Dambreak wave impact\n5. Coastal engineering
User Answer	\u2022A resolved coupling model to directly simulate interaction between two-phase fluids and irregularly shaped particles.\u2022The irregularly shaped particles are modeled by multi-sphere clumps in DEM.\u2022A number of benchmark cases are conducted and compared with experimental works.\u2022A case study of dambreak wave impact on a rock pile demonstrates the model's potential to coastal engineering.
TAM	\u2022Resolved coupling model is developed to simulate two-phase fluid interactions with multi-sphere clumps.\u2022The model can be applied in a wide range of particle sizes and concentrations.\u2022Benchmark cases show good agreement between simulation results and experimental data.\u2022Dambreak wave impacts on single sphere, cluster of spheres and cylinder are investigated.\u2022Applications include coastal engineering, sediment transport and environmental studies.
OPPU	\u2022Resolved coupling model is developed to simulate two-phase fluid interactions with irregularly shaped particles.\u2022Multi-sphere clumps are used as a surrogate of real particles in simulations.\u2022Benchmark cases show that the proposed method can capture the particle motion and sediment transport accurately.\u2022Dambreak wave impacts on multi-particle bed, and dune formation process are investigated by the present model.\u2022The results provide useful insights into coastal engineering problems involving complex geometries.
CoPe (ours)	\u2022A resolved coupling model is proposed to simulate two-phase fluid interactions with irregularly shaped particles.\u2022The multi-sphere clumps method is used to represent the irregularly shaped particles.\u2022Benchmark cases are conducted to verify the accuracy of the proposed model.\u2022Dambreak wave impact on a rigid cylinder and a rough surface is simulated by the proposed model.\u2022The results show that the proposed model can be applied in coastal engineering.

Figure 7: **Qualitative example for Abstract Generation**

Review Writing	
Query	Generate the review text written by a reviewer who has a given an overall rating of \"4.0\" for a product with description \"In the taut thriller, when Nancy (Blake Lively) is surfing on a secluded beach, she finds herself on the feeding ground of a great white shark. Though she is stranded only 200 yards from shore, survival proves to be the ultimate test of wills, requiring all of Nancys ingenuity, resourcefulness, and fortitude.\". The summary of the review text is \"I found myself holding my breath in certain spots and actually willing her to survive. That is the sign of a good movie.\".
User Answer	Im gonna get off this rock. Im gonna fight. Nancy (Lively) has just lost her mom and travels to her favorite place in the world in order to hopefully reconnect with her one last time. What begins as a relaxing beach getaway takes a terrifying turn when she swims right into the feeding ground of a Great White Shark. Now, with a severely bitten leg and a tiny rock just above the water line Nancy must survive long enough for someone to find her, but she isn't the only one fighting for survival. This is a very tense movie that is scary in the fact that this is something that could actually happen. Looking back on the movie I realized there wasn't a whole lot of dialog but I didn't notice it when I was watching. You really feel for her and live and die with every scene. I found myself holding my breath in certain spots and actually willing her to survive. That is the sign of a good movie. The movie defiantly has the feel of Open Water and if you like movies like that you will enjoy this as well. Overall, the way the movie makes you feel makes this more of an experience than a movie. I liked this a lot more than I expected to. I give this a B+.
TAM	I'm not sure what it says about me that this film had me so engrossed. It was like watching a train wreck unfold before your eyes. A young woman goes out into the ocean alone while her boyfriend surfs. She gets attacked by a shark and then spends hours trying to get back to land. There isn't much dialogue or action but there were moments where I literally held my breath as she tried to swim away from the shark. This is one of those films you watch because you know something bad is going to happen and you want to see how it plays out. I don't think I would have watched it if I didn't already own it. But once I started I couldn't stop until the end. Blake Lively does a very good job playing someone who is terrified yet determined to live through this experience. If you enjoy suspenseful movies, give this one a try
OPPU	"Ive been bitten before but never like this. After being attacked by a Great White Shark while swimming alone at sea Nancy (Lively) struggles to stay alive until help arrives. This was not what I expected. Going into it I thought that there would be lots of blood and gore and a lot of suspense. While there were some tense moments the movie was more about how one woman copes with the situation rather then just trying to get away. There really wasn't much gore or anything like that so if you are looking for a horror type movie this may disappoint you. On the other hand though this was very intense and kept me interested throughout. I did find myself holding my breath in certain spots and actually willing her to survive. That is the sign of a good movie. Overall, a very interesting take on a shark attack story. I give this a B+."
CoPe (ours)	"Ive been bitten by a shark! Nancy (Lively) is out surfing alone when she is attacked by a shark. She manages to get back to shore but not before being injured. When she realizes that help is not coming she must find a way to stay alive until someone comes along. This is a very tense movie. It is hard to make a movie about one person trying to survive against something else without it getting boring or repetitive. This one does a pretty good job of keeping you interested and involved in what is happening. There are some parts that drag a little but for the most part this is a really good movie. Blake Lively does a great job in this and makes you feel everything she is feeling. Overall, a very tense and exciting movie that keeps you guessing and wondering if she will make it. I give this a B+.

Figure 8: **Qualitative example for Review Writing**

Topic Writing	
Query	Generate the content for a reddit post Indoor cat doesn't like car ride or outdoors, tries to kill me, cat poo in car preferable.
User Answer	You got off lucky. When I was in college, one of my roommates had a cat that would spend all day on the windowsill, staring out the window (it was an indoor cat). I decided one day it would be nice to drive the cat to the park to let it experience the outdoors for its first time. In the car, it tried to shred my shoulder, and then camped out under the brake pedal, almost causing me to wreck. At the park, it just cowered and wouldn't move. On the ride home, it decided the best place to be was on top of my head, using its claws for purchase.
TAM	I have an indoor/outdoor cat that is about 10 years old now and she has always been very skittish around people (she was found as a stray when she was younger). She will not let anyone pick her up unless they know how to handle her properly. If you try to grab her by the scruff of the neck she will bite your hand off. So we just pet her on the head and rub her belly until she calms down enough to be picked up. We also keep her nails trimmed so she can't do any real damage if she does decide to attack. \n The problem is that my wife wants to take our cat with us when we go camping this weekend but I am worried because she hates being in cars and hates going outside. When we first got her she would hide under the bed whenever someone came over and wouldn't come out until everyone left. Now she comes out from time to time but still only likes to stay inside. \n My question is what should I do? Should I put her in a carrier and hope for the best? Or should I leave her at home? Also, if it helps, she has never had diarrhea before and she is litter trained.
OPPU	I have an indoor/outdoor cat that hates being outside and hates riding in cars. He is also very smart (and has been known to open doors). One day we were going on vacation and he was not allowed to come with us because of his issues. We put him in a carrier and took it into our bedroom so he wouldn't be able to see us leave. When we got back from vacation, he had somehow gotten into the house while we were gone, found the carrier, opened it up, climbed inside, and then proceeded to shit all over himself and the box. Then he waited until we came home, walked around the corner when we entered the room, and jumped at my face as hard as he could. It knocked me off balance and I fell onto the bed. The little bastard ran away before I could get my hands on him.
CoPe (ours)	I was driving my mom's car with her cat in it. The cat had been an indoor cat all of its life and didn't like being in the car. It kept trying to get out through the window (it wasn't rolled down). So I put on some gloves and held onto him so he couldn't escape. He then proceeded to try to claw my eyes out. \n 2) I was driving home from work one day when I saw a cat sitting in the middle of the road. I stopped and got out to move it off the road. As soon as I touched it, it started spraying pee everywhere. I quickly dropped it back into the street and drove away.

Figure 9: **Qualitative example for Topic Writing**