Unlearning Misalignment for Personalized LLM Adaptation via Instance-Response-Dependent Discrepancies Journal Submissions

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Abstract

While Large Language Models (LLMs) have revolutionized chatbot interactions, they often fall short in aligning responses with the nuanced preferences of individual users—a challenge rooted in the inherently subjective and proprietary nature of user preferences. Consequently, prompt-based learning, though effective in enhancing factual accuracy due to its emphasis on universal correctness, remains insufficient for achieving accurate personalised response alignment. Because user preferences vary widely across individuals and contexts, aligning responses requires a more personalized and context-aware approach. To address this limitation, we propose Consistent Marginalization (CM)—a novel framework that aims to unlearn misalignment by constructing a personalised memory bank of instance-response-dependent discrepancies, built from a small set of user preference samples. This personalised memory bank equips LLMs with the ability to understand, recall, and adapt to individual preferences, enabling more consistent and personalized responses. Evaluated across a diverse range of domain-specific datasets and model architectures, CM yields notable improvements in response alignment and robustness. We believe Consistent Marginalization represents a valuable step toward enabling LLMs to become genuinely personable and adaptive conversational agents by understanding user preferences and generating responses that are better aligned with individual user expectations.

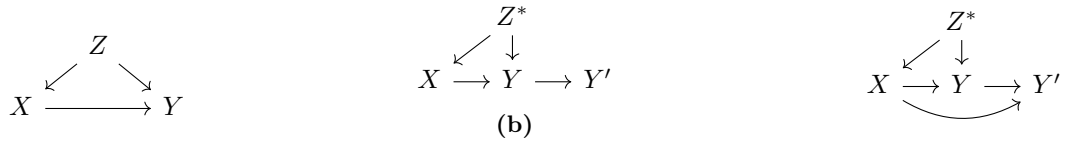
1 Introduction

Autoregressive large language models (LLMs) have recently achieved widespread adoption due to their remarkable performance across various domains (Brown et al., 2020; Touvron et al., 2023; OpenAI, 2023). These models are predominantly trained via next-token prediction objectives targeted at maximizing output accuracy (Devlin et al., 2018; Touvron et al., 2023; Hu et al., 2024). However, as LLMs become increasingly employed in personalized applications, requiring alignment with nuanced and individual user preferences, their outputs frequently diverge from anticipated or preferred responses Zhao et al. (2025). Such deviations—often characterized as hallucinations—lead to misaligned or undesired outputs, presenting substantial challenges in applications requiring adaptive and personalized supervision, including recommendation systems, personalized response generation, and text mining, where consistency, reliability, and alignment with individual expectations are critical Wu et al. (2024). While the effectiveness of LLMs is closely tied to the prompt strategies employed—serving as external guidance for self-correction (Brown et al., 2020; Wei et al., 2021; Yao et al., 2022; Liu et al., 2023)—these strategies are primarily designed to ensure **output accuracy**, rather than **personalized response alignment**. Figure 1 highlights two separate learning objectives: response alignment—how well an LLM reflects subjective, user-specific preferences—and output accuracy—the objective factual correctness of its content. Standard prompt-based learning (Figure 1a) optimizes for output accuracy but neglects instance-response independent and dependent discrepancies—misalignment between user intent and model response — illustrated in Figures 1b and 1c. Ignoring these discrepancies leads to persistent misalignment, underscoring the need for mechanisms that can record, recall, and correct personalised response misalignment between the user and LLM. Aligning large language models

(LLMs) to generate responses tailored to individual users is challenging because it requires understanding and incorporating user preferences. Unlike complex reasoning tasks, which are objective due to their basis in facts and definitive solutions, user preferences are inherently subjective, reflecting personal opinions and judgments (Hu et al., 2024). While supervised fine-tuning on comprehensive datasets can achieve such alignment, it is often costly, and many user-specific datasets are valuable only to the individual, limiting their applicability to the broader community.

Consider a user interacting with a financial LLM assistant. In an earlier conversation, the user states, "I'm highly risk-averse and prefer capital-preservation strategies." Later, the same user asks, "Could you recommend an investment portfolio for the next 1 months?" An LLM that has not been fine-tuned or lacks personalized memory may suggest high-risk assets—such as "invest 80% in cryptocurrency"—because recent returns make them appear objectively justifiable. This recommendation reveals a personalized response misalignment between the user's low-risk objective and the model's high-risk recommendation. If this mismatch is stored in a personalized memory bank as a response discrepancy, the LLM can retrieve it the next time the user poses a finance-related question. Seeing that the user consistently rejects high-risk ideas, the model can infer a latent preference for safety and propose a low-risk investment—such as an government bonds. By recalling and correcting past misalignments, the assistant can aligns its advice with the user's individual risk tolerance rather than defaulting to generic, return-maximizing recommendations. Prompt-based self-reflection and self-correction alone (Paul et al., 2023; Shinn et al., 2023; Bang et al., 2023; Li et al., 2023; Zhou et al., 2023; 2022) struggle to achieve such personalized alignment, especially when rich user feedback are scarce. Moreover, even in tasks focused on output accuracy, intrinsic self-correction remains limited when models rely exclusively on their own outputs for feedback (Huang et al., 2023; Hu et al., 2024). Overall, the goal of this work is to:

- **Equip LLMs to remember and consistently follow each user's preferences, ensuring their responses remain aligned over time.**



(a) Standard-Prompt-Based Approach with Z (equation 1)

(b) ***Instance-Response-Independent Discrepancies*** with Optimal Z^*

(c) ***Instance-Response-Dependent Discrepancies*** with Optimal Z^* (equation 1)

Figure 1: **Contrasts standard prompt with Consistent Marginalization (CM) framework and underscores why accounting for instance–response-dependent discrepancies is necessary to bridge the gap between LLM-generated responses and user-preferred responses.** In standard API-based prompt, given an input X to a Large Language Model (LLM), it is assumed that the desired output, or user-preferred responses Y, can be obtained by identifying a latent variable Z representing the prompt strategy. Consistent marginalization acknowledges that the LLM's generated responses can deviate from the user-preferred responses Y, which is denoted as Y', even for a given input X and an optimal latent variable Z^*. Our method explicitly considers these discrepancies and aims to construct a personalised memory bank of the discrepancies between Y and $Y^{'}$, given X and Z. We distinguish **two types of response discrepancies**: one of which is **instance-response independent discrepancies** shown in Figure 1(b), where Y' is independent of X, and other one is **instance-response dependent discrepancies** shown in Figure 1(c), which is a more realistic scenario. Our study focuses on the latter instance-response *dependent* discrepancies. Assuming that the optimal Z^* has already been determined, our primary learning objective is to estimate $p(Y' \mid Y, X)$. This probability shows the discrepancies between the user-preferred responses Y and the LLM-generated responses Y' under given X.

To overcome the limitations, we introduce Consistent Marginalization (CM). This method mitigates misalignment between a large-language-model (LLM) and an individual user's preferred response in a low-data regime without any full user-specific dataset fine-tuning. CM tackles the two fundamental obstacles that

prevent off-the-shelf LLMs from delivering truly personalised aligned responses: (i) preference recognition, since current models often fail to detect a user's latent preferences Zhao et al. (2025), and (ii) preference retention, because even when a preference is conveyed once, the model does not remember it in later turns. We argue that both shortcomings stem from overlooking instance–response–dependent discrepancies during pre-training or the prompt. CM resolves them by (i) explicitly estimating the discrepancy between an LLM's response and the user's preferred response, and (ii) storing these discrepancies in a lightweight "personalised memory bank." During future interactions, the model consults this bank, recalls past misalignments, and self-corrects—achieving strong personalization with only a small set of preference examples and no per-user fine-tuning. Our experimental results validate the effectiveness of the Consistent Marginalization (CM) method. The main contributions include:

- **A general framework for personalised response alignment.** We introduce CM, a method that accounts for instance-dependent discrepancies to mitigate misalignment between an LLM and an individual user's preferred response in data-constrained settings—without any full, user-specific fine-tuning.
- **A probabilistic formulation for unlearning misalignment**. CM performs principled, amortised inference of user preferences in a low-data regime by marginalising instance-response discrepancies between the LLM and the user.
- **Demonstrated effectiveness on large-scale datasets with multiple open and closed-sourced LLMS**. We validate our method on multiple user preference-related large-scale datasets. The experimental results demonstrate its effectiveness in enhancing the user personalised response alignment of LLMs without fine-tuning, indicating broad applicability.

2 Related Works

2.1 Prompt-based learning

Prompt-based learning, first popularised by Brown et al. (2020), shows that a handful of in-context examples can nudge an LLM toward more accurate responses. Subsequent prompt-engineering methods—instruction tuning (Wei et al., 2021), chain-of-thought (Cot) prompt (Wei et al., 2022), and ReAct (Yao et al., 2022)—inject explicit task structure or external tool calls to improve reasoning further. Active Prompt (Diao et al., 2023), Generate-Knowledge Prompting (Liu et al., 2023), and Consistency Prompting (Wang et al., 2023) curate clarifying questions, external facts, or multi-path consensus so that the final answer is more consistent and accurate. A parallel line of research explores *self-correction*: Self-Refine (Madaan et al., 2024) and Tree-of-Thought (Tot) (Yao et al., 2024; Long, 2023) allow the model to iteratively critique and revise its own outputs. Reflexion (Shinn et al., 2023) introduces external tools to validate self-generated feedback and maximise accuracy, but obtaining tools that can assess personalised response alignment at scale remains challenging. Moreover, Huang et al. (2023) shows that self-generated feedback can actually reduce quality when no external check is available, making previous methods less effective for personalised response alignment. However, these methods still fall short on two fronts that are central to personalised response alignment: (i) they do not tackle fine-grained *preference recognition* at the instance level, and (ii) they lack a *memorisation mechanism* that would let the LLM remember and reuse past preference signals over time. Our work addresses both gaps.

2.2 User Instance-Response-Dependent Discrepancies Estimation

Several related works Yang et al. (2022); Han et al. (2018); Patrini et al. (2017) leverage instance-*independent* transition matrices to achieve consistent classifiers. These transition matrices, which resemble response instance-independent discrepancies. However, such methods generally rely on a **white-box setting**, where model parameters are directly accessible. This accessibility enables the estimation of transition matrices in *probabilistic forms* rather than discrete forms. Despite their effectiveness in white-box scenarios, these approaches have not addressed the accurate estimation of instance-response dependent discrepancies, which capture finer-grained relationships between model outputs and user preferences. Addressing this gap is

essential for enabling robust, personalized response alignment in real-world applications, particularly when working with sourced **black-box models** such as open and close-sourced large language models (LLMs).

3 Problem Setting

3.1 Preliminaries

Let X denote a user query, expressed as a natural language question. The desired response, provided a priori by the user, is denoted as Y. Notably, Y is not generated by the large language model (LLM) but is instead a user-specified reference. A latent variable Z represents the prompt strategy to guide the LLM's generation process. While Z is instrumental in aligning the LLM's response with the user's expectations, it alone is insufficient to guarantee perfect alignment. The LLM-generated response, given X and the chosen Z, is represented as Y'. Discrepancies between the user desired response Y and the generated response Y' are represented and stored using a deterministic transition matrix $M_{(X)_{Y',Y}}$ (See Section 4.1).

3.2 Notation

We define a feature space $\mathcal{X} \subseteq \mathbb{R}^d$ and a label space $\mathcal{Y} = \{1, \ldots, c\}$, where c is the total number of response classes. Each instance $X \in \mathcal{X}$ is associated with a true response $Y \in \mathcal{Y}$ and a generated response $Y' \in \mathcal{Y}$. Here, the user's preferred response Y is treated as the true response. In many real-world scenarios, full supervision is unavailable for the entire dataset. Instead, there is usually a small subset of cleanly labelled samples alongside a larger set of unlabeled data. More specifically, we can define D_{User} as the distribution of the cleanly labelled small sample set, denoted as user-preference sample, which contains pairs $(X, Y, \vec{Y})$ where $\vec{Y} = \mathcal{Y}$, representing a candidate label set encompassing all responses. This can be expressed as $\{(X_i, Y_i, \vec{Y})\}_{i=1}^{s}$, with s being the total number of clean samples. We define D_{large} as the distribution for the large unsupervised dataset, denoted as $\{X_i, \vec{Y}\}_{i=s+1}^{n}$, where n is the total number of both labelled and unlabeled training samples. The D_{large} is considered an unsupervised dataset, meaning neither a ground truth response nor weak supervision is associated with each instance in the distribution. The learning objective is to design a prompt strategy that leverages D_{User}, which constitutes about 5% of the total training samples, to allow large language models (LLMs) to accurately annotate the large unsupervised dataset D_{large}.

4 *Incorporating* LLM–User Response Dependent Discrepancies via Marginalisation

Most recent work on prompt engineering focus on designing or searching for effective prompt schemes —e.g., chain-of-thought or tool-augmented prompts—to maximise the conditional likelihood $p(Y \mid X)$ of an LLM (Wei et al., 2022; Yao et al., 2022). The conventional approach of Hu et al. (2024), which *does not* account for personalised response misalignment, is

$$p(Y \mid X) \;=\; \sum_{Z} p(Z, Y \mid X) \;=\; \sum_{Z} p(Y \mid X, Z)\, p(Z \mid X), \tag{1}$$

where $p(Y \mid X)$ is the likelihood of the sequence generated by the LLM, and Z indexes a family of prompts (or latent reasoning paths). Equation equation 1 corresponds to the *ideal*, personalised response misalignment-free setting in which the model's response Y' is always aligned to the user-preferred response Y. In practice, however, even an optimal prompt Z^* may be inadequate for personalisation if the LLM has not been pre-trained or fine-tuned on user-specific data. Therefore, in its unmodified form, the formulation in equation 1 is ill-suited to personalised response-alignment tasks because it ignores the response discrepancies between LLM outputs and user preferences. This paper addresses that gap.

Instance–Response Dependent Discrepancies via Marginalisation Let the latent variable Y' denote the *misaligned* response produced by the LLM for input X under prompt Z. By modelling Y' explicitly, we can learn—and later marginalise—the instance–response dependent discrepancy between Y' and the

user-preferred response Y. We therefore revise the formulation as follows:

$$p(Y \mid X) = \sum_{Z} \sum_{Y'} p(Z, Y, Y' \mid X) = \sum_{Z} \sum_{Y'} p(Z \mid X)\, p(Y \mid X, Z)\, p(Y' \mid Y, X, Z) \tag{2}$$

$$\overset{\text{(i)}}{=} \sum_{Z} \sum_{Y'} p(Z \mid X)\, p(Y \mid X, Z)\, p(Y' \mid Y, X) \tag{3}$$

$$= \sum_{Z} p(Z \mid X)\, p(Y \mid X, Z) \underbrace{\sum_{Y'} p(Y' \mid Y, X)}_{\substack{\textbf{Instance-Response} \\ \textbf{Dependent Discrepancies}}} . \tag{4}$$

Step (i) assumes the conditional-independence $Y' \perp\!\!\!\perp Z \mid (Y, X)$. This assumption is reasonable, as our goal is to recover an unbiased estimate of LLM misalignment, capturing how the LLM responds to a user query without being undermined by external factors such as the specific prompting strategy. The final factor $p(Y' \mid Y, X)$ is denoted as *instance–response-dependent discrepancies*. Our aim is to estimate the $p(Y' \mid Y, X)$ to maximise the conditional likelihood of LLM in producing personalised responses that align with user preferences. Our formulation explicitly covers the realistic case in which the LLM's raw response Y' is misaligned from the user-preferred response Y. When those instance–response-dependent discrepancies are shown, we estimate the $p(Y' \mid Y, X)$ and utilise it to endow the LLM to align more with the user. In the hypothetical, perfectly aligned regime where $Y' = Y$ for every input, the discrepancy distribution reduces to an identity matrix $p(Y' \mid Y, X) = \mathbf{1}_{\{Y'=Y\}}$. Under the scenario, our framework naturally reduces to equation 1. Because our learning objective is discrepancy estimation rather than prompt optimisation, we assume a suitable prompt Z^* has already been given. The joint model for the user-preferred response Y and the LLM's misaligned response Y' then factorises as

$$p(Y \mid X) = \sum_{Y'} p(Z^*, Y, Y' \mid X) \;=\; \underbrace{p(Z^* \mid X)}_{\textbf{Optimal prompt}} \; \underbrace{p(Y \mid X, Z^*)}_{\textbf{User-Preferred Response}} \; \underbrace{\sum_{Y'} p(Y' \mid Y, X)}_{\substack{\textbf{Instance-Response} \\ \textbf{Dependent Discrepancies}}} . \tag{1}$$

To obtain the user's preferred response by searching Z^* is indeed essential but insufficient. In this paper, our goal is to estimate the term $\sum_{Y'} p(Y' \mid Y, X)$, which quantifies the discrepancies between LLM outputs and user preferences for all instances with their corresponding true labels Y by marginalizing over all possible LLM-generated responses Y'. Given that $p(Y \mid Z^*, X)$ and $p(Z^* \mid X)$ are either known or given, the task of maximizing $p(Y \mid X)$ ultimately depends on accurately estimating $\sum_{Y'} p(Y' \mid Y, X)$. The $p(Y \mid Z^*, X)$ and $p(Z^* \mid X)$ are assumed obtainable since we assume Z^* is given. $p(Y \mid Z^*, X)$ describes how likely each possible Y is, given the input X and the optimal prompt strategy Z^*. However, this distribution alone does not guarantee that the LLM will produce the ground truth response in practice. The model's generated output Y' can still deviate from Y due to inherent uncertainties or imperfections in the LLM. To address this issue, it is crucial to consider the discrepancy distribution $p(Y' \mid Y, X)$ and incorporate it into the inference process. By consistently marginalizing over all possible generated responses Y', we can more accurately model the process by which the true label Y relates to the observed LLM output Y'. This leads to a more reliable and coherent inference framework that accounts for the discrepancy between the idealized distribution $p(Y \mid Z^*, X)$ and the practical reality of the LLM's response generation. Therefore, the conditional likelihood $p(Y \mid X)$ can be maximised if $\sum_{Y'} p(Y' \mid Y, X)$ can be correctly identified.

4.1 Instance-Response-Dependent Discrepancies Between LLMs and User

This subsection *bridges theory and implementation*: we show how the notion of response misalignment formalised by $\sum_{Y'} p\big(Y' \mid Y, X\big)$ is realised in practice and subsequently exploited.

Definition of misalignment. For a fixed query X and ground-truth label Y, the probability $p(Y' \mid Y, X)$ which we denote as the *instance–response-dependent discrepancy*—quantifies how often the LLM produces

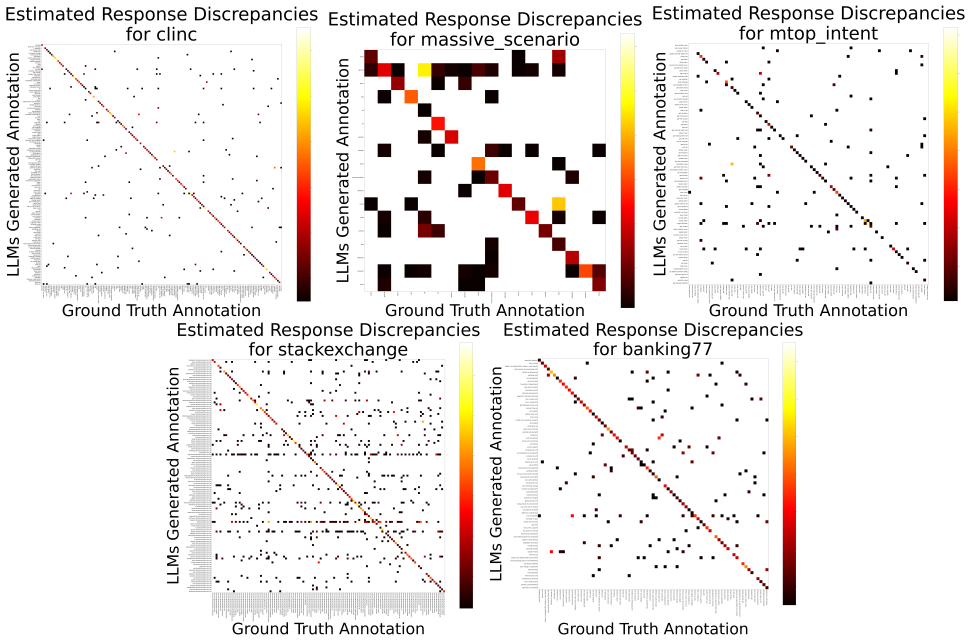


Figure 2: Estimated Instance-Response-Dependent Discrepancies on ChatGPT 3.5 Turbo for datasets StackExchange(Topic) CLINC150(Intent), Banking77(Intent), MOTE(Intent), Massive(Scenario).The diagonal entries of the matrix indicate the aligned responses from LLMs given each dataset, whereas the other highlighted entries indicate misaligned responses. *The annotation also can be denoted as response.*

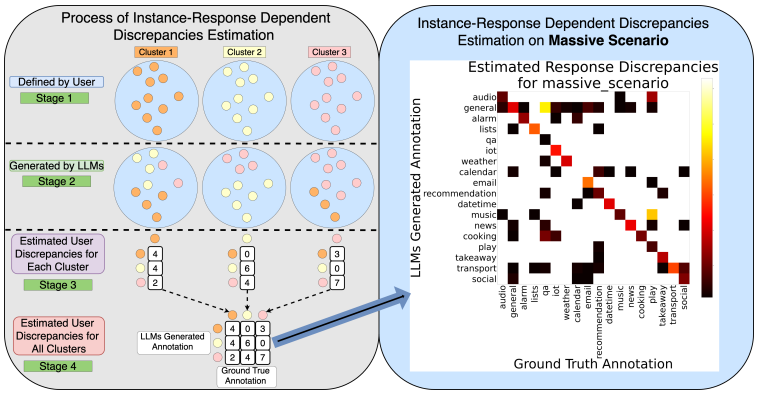


Figure 3: Semantic Depiction of Instance-Response Dependent Discrepancy Estimation. Clusters indicate instances with the same responses.

each (possibly mis-aligned) response Y'. We instantiate the $p(Y' \mid Y, X)$ via a *deterministic* transition matrix $M(X) \in \{0,1\}^{|\mathcal{Y}| \times |\mathcal{Y}|}$ whose entry $M(X)_{k',k} = 1$ iff, at least once in the interaction history for query X, the LLM produced response $Y' = k'$ while the ground-truth label was $Y = k$. Each column k therefore encodes the set of previously observed alignments ($k' = k$) and misalignments ($k' \neq k$) associated with $Y = k$ given X. During our experiments we treat $M(X)$ as an *personalised memory bank* rather than a binary mask. Formally,

$$M_{(X)_{k',k}} = \begin{cases} 1, & \text{if there exists a user preference sample } i \text{ such that } Y_i = k \text{ and } Y'_i = k' \\ 0, & \text{otherwise.} \end{cases}$$

Ideally, only the diagonal entries of $M_{(X)}$ would be positive, indicating that the LLM's generated responses match the true responses ($Y = Y'$). All **off-diagonal** entries would remain zero, indicating perfect response

alignment. In practice, however, discrepancies arise which represent instances where the LLM's responses deviate from the true responses in the user preference samples, resulting in **nonzero off-diagonal** elements that capture the discrepancies between true responses and the LLM-generated responses. Each **row** of the estimated matrix $M_{(X)}$ encodes the dependency between the LLM's generated responses Y' and the possible true labels Y. Specifically, $M_{(X)}$ records all past discrepancies observed for instances sharing the same true label Y. This dependency is utilized to truncate the candidate label set for each sample based on the LLM's responses. Formally, M is defined as a $K \times K$ deterministic transition matrix (where K is the number of classes) with elements $M_{k',k}$, where: For example: $M_{(X)_{1,1}} = 1$ indicates that the LLM predicted responses 1 given the true responses was 1, meaning that there are no response discrepancies. $M_{(X)_{4,1}} = 1$ indicates that the LLM predicted responses 4 given the true responses was 1, meaning that there are response discrepancies. For illustration purposes, consider the following example of the deterministic transition matrix $M_{(X)}$:

$$M_{(X)} = \begin{bmatrix} M_{1,1}| & M_{1,2}| & M_{1,3}| & M_{1,4}| \\ M_{2,1}| & M_{2,2}| & M_{2,3}| & M_{2,4}| \\ M_{3,1}| & M_{3,2}| & M_{3,3}| & M_{3,4}| \\ M_{4,1}| & M_{4,2}| & M_{4,3}| & M_{4,4}| \end{bmatrix} = \begin{bmatrix} 1| & 0| & 0| & 1| \\ 0| & 1| & 0| & 0| \\ 0| & 1| & 1| & 0| \\ 1| & 0| & 0| & 1| \end{bmatrix}. \tag{5}$$

The ***highlighted entries*** denotes previously made misalignments by LLMs recorded for all instances with respect to each true responses Y. We treat each true responses as a category, thereby aggregating all possible misalignments of the instances made by LLMs associated with that category. In this deterministic transition matrix, $M_{(X)_{k',k}}$ indicates that the LLM predicted responses k' when the ground-truth responses was k for at least one observed sample. Each **row** of $M_{(X)}$ corresponds to a predicted label $Y' = k'$, and each **column** corresponds to a ground-truth label $Y = k$. The entry $M_{(X)_{k',k}} = 1$ indicates that the LLM has generated the response $Y' = k'$ when the true label was $Y = k$. This can be described as follows:

Condition 1: $k' = k$ (Response Agreement). If $k' = k$, the LLM's prediction aligns with the true label, indicating no discrepancy:

$$M_{(X)_{k',k}} = 1 \quad \text{(LLM's prediction matches the true label } Y = k\text{)}.$$

Condition 2: $k' \neq k$ (Response Discrepancies). If $k' \neq k$, the LLM has generated an incorrect response $Y' = k'$ for instances where the true label is $Y = k$. This captures a discrepancy:

$$M_{(X)_{k',k}} = 1 \quad \text{(LLM's prediction } Y' = k' \text{ does not match the true label } Y = k\text{)}.$$

By estimating the $M_{(X)}$ from user preference samples D_{User}, we record all possible past misalignments (Y') made by the LLM for instances with the corresponding true response Y. This matrix provides a structured representation of the alignment or discrepancies between the LLM's responses and user-preferred responses. Given new inputs, the deterministic transition matrix $M_{(X)}$ and the initial responses from the LLM, we can refine the prediction process as follows: By treating the initial prediction Y' as an index, $M_{(X)}$ allows us to retrieve the set of potential correct responses Y associated with Y' during the estimation phase. This enables the LLM to reconsider its prediction by selecting only from the refined candidate set, effectively recalling past misalignments. To summarise and connect the theoretical construction with our practical implementation, we add the following. The $M(X)_{k',k}$ records every aligned ($k' = k$) and mis-aligned ($k' \neq k$) occurrence, we can obtain an *empirical conditional distribution* of misalignment and alignment via simple row normalisation: $p\big(Y' = k' \mid Y = k, X\big) = \widetilde{M}_{(X)k',k} := \frac{M(X)_{k',k}}{\sum_{j \in \mathcal{Y}} M(X)_{j,k}}$ whenever $\sum_j M(X)_{j,k} > 0$. In practice, however, our LLM is a **black-box**: its parameters, loss function, and internal soft-max layer are inaccessible. Subsequently, we cannot train the LLM using estimated $\widetilde{M}_{(X)}$.

4.2 Example: Personalizing LLM Responses to User Preferences

This following example illustrates the complete instance-response-dependent discrepancy-estimation pipeline. Each user query X_i is initially paired with an candidate set $\vec{Y}_i$ that lists *all* potential responses. Our aim is to steer the LLM toward responses that faithfully reflect individual user preferences across the unlabeled corpus D_{large}. **Consistent Marginalisation (CM).** CM first *estimates* instance–response-dependent discrepancies

between the LLM's misaligned response Y_i' and the ground-truth preference Y_i. Because full supervision is impractical, these discrepancies are infers from a small but reliable set of annotated preference samples, storing them in a transition matrix $M_{(X)}$. This matrix acts as a lightweight *personalised memory bank* that records how—and how often—the model has deviated from user intent. At inference time, $M_{(X)}$ is exploited to refine the original candidate set $\vec{Y}_i$, generating a pruned set $\vec{Y}_{i,\text{Updated}}$ that excludes potentially unwanted responses. The LLM then generates a final response $\bar{Y}_{i,\text{Refined}} = G(X_i, \vec{Y}_{i,\text{Updated}})$, which is statistically more likely to align with the user's stated preference.

Instance-Response Dependent Discrepancy Estimation. Let $D_{\text{User}} = \{(X_i, Y_i)\}_{i=1}^{s}$ denote a small set of user preference samples, where $s = 4$. Each input X_i has a known ground-truth label Y_i. From these samples, we construct a deterministic transition matrix M, which captures mappings between the LLM's generated responses Y_i' and the corresponding ground-truth labels Y_i. We also define the unlabeled dataset as $D_{\text{large}} = \{X_i\}_{i=1}^{N}$, with $N = s = 4$ in this illustrative example. Let $\vec{X} = \{X_1, X_2, X_3, X_4\}$ be the set of input queries, and let $\vec{Y}_{\text{Query}} = \{\vec{Y}_1, \vec{Y}_2, \vec{Y}_3, \vec{Y}_4\}$ denote the initial candidate sets for each query. Assuming a known label space of size K, each $\vec{Y}_i$ is initialized to the same universal candidate set $\vec{Y} \in \{0,1\}^K$, where all entries are initially set to one—i.e., every class is a potential candidate. We define $Y_{\text{True}} = \{Y_1, Y_2, Y_3, Y_4\}$ as the set of one-hot encoded vectors representing ground-truth responses. Using this setup, the personalised memory bank $M(X)$ is estimated from D_{User} and subsequently used to refine the prediction space for the LLM during inference, producing a final output $\bar{Y}_{i,\text{Refined}} = G(X_i, \vec{Y}_{i,\text{Updated}})$.

$$\vec{Y}_{\text{Query}} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix} \quad Y' = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \end{bmatrix} \quad \vec{Y}_{\text{G}} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad M_{(X)} = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 1 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} \text{Given LLMs Generated Response } Y_i' \text{ on } \vec{X}_i & \\ \quad \text{If LLM generated response is } 1 & \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \\ \quad \text{If LLM generated response is } 2 & \\ \quad \text{If LLM generated response is } 3 & \\ \quad \text{If LLM generated response is } 4 & \end{bmatrix}$$

In the right-hand-side matrix, the estimated $M_{(X)}$ represents the potential user-preferred response $\vec{Y}_{i_{\text{Updated}}}$ for $\vec{X}_i$ corresponding to different LLM-generated responses. $\vec{Y}_G$ denotes the ground truth responses with respect to X. If the LLM generates response $Y' = k$, then $\vec{Y}_{i_{\text{Updated}}}$ will be the k-th row of the matrix $M_{(X)}^{Y_1}$. This rule applies to all LLM-generated responses and significantly reduces the candidate set of responses from $[1,1,1,1]$ to a one-hot vector (e.g., $[1,0,0,0]$ if $k = 1$). **Inference.** Our goal is to enable the LLM to recall and generate the correct response for each query X_i from the corresponding candidate set $\vec{Y}_i$, transforming $\vec{Y}_{\text{Query}}$ into $\vec{Y}_{\text{Refined}}$. Ultimately, after $M_{(X)}$ has been estimated, given a LLM, denoted as G, then takes an unannotated data point X_i from D_{Large} and $\vec{Y}_{i_{\text{Updated}}}$ which is inferred using $M_{(X)}$ as input to produce a refined responses $\bar{Y}_{i_{\text{Refined}}} = G(X_i, \vec{Y}_{i_{\text{Updated}}})$. The goal is to ensure that $\bar{Y}_{i_{\text{Refined}}}$ matches the true class label $Y_{i_{\text{True}}}$ for each X_i.

5 Selection Criterion for User-Preference Samples

In practice, selecting a small subset of samples (hereafter referred to as "user preference samples") from a large training set is challenging. **High Confidence from Human Annotators:** In parallel, we select samples for which human annotators have high confidence in their preferred responses. Formally, consider an instance X and a label Y drawn from the label set $\vec{Y}$. A user preference sample must satisfy $p(Y \mid X, \vec{Y}) \approx 1$, indicating that the human annotator is certain of their responses. This criterion ensures that the user preference samples are as misalignment-free as possible, minimizing uncertainty and reducing the risk of propagating incorrect user preferences into the learning process. Since our setting assumes the availability of a small set of

user-preferred responses, we do not conduct an extensive feasibility study on the selection process. Instead, we adopt this selection criterion as a working assumption, ensuring that the chosen user preference samples are reliable (from the human annotator's perspective). *Section 4* shows that *instance–response-dependent discrepancies* are essential for aligning LLM response with user preference. We now describe how to estimate $\sum_{Y'} p(Y' \mid Y, X, \vec{Y})$ and specify the assumption of user-preference samples for the estimation under which alignment can be achieved without per-user fine-tuning. Because the candidate set $\vec{Y}$ is deterministic in our setting, it appears explicitly in the conditional notation to ensure the estimation procedure is clear.

Definition 1 (LLM misaligned Response)**.** Let G denote the LLM. For a query X and candidate set $\vec{Y}$,

$$p(Y' \mid X, \vec{Y}) \;=\; G(X, \vec{Y}), \tag{6}$$

where Y' may differ from the user-preferred response Y.

Proposition 1. Because every model output Y' is paired with (possibly latent) Y, we have

$$\underbrace{p(Y' \mid X, \vec{Y})}_{\text{LLM-Generated Response}} \;=\; \underbrace{\sum_{Y} p(Y' \mid Y, X, \vec{Y})}_{\substack{\textbf{Instance-Response}\\ \textbf{Dependent Discrepancies}}} \underbrace{p(Y \mid X, \vec{Y})}_{\text{User-Preferred Response}} . \tag{7}$$

Assumption 1 (High-Confidence User Preference Samples)**.** There exists a finite set

$$\mathcal{D}_{\text{User}} = \{(X_i, Y_i)\}_{i=1}^{s},$$

for which $\Pr(Y = Y_i \mid X_i, \vec{Y}) = 1$ for all i.

Corollary 1 (Discrepancy Estimation)**.** Under Assumption 1, pairing each ground-truth Y_i with its model output Y_i' enables estimation of $p(Y' \mid Y, X, \vec{Y})$.

Example 1. If $Y = 1$ is known for X_1 with certainty $\big(p(Y = 1 \mid X_1, \vec{Y}) = 1\big)$, then

$$\underbrace{p(Y' = 2 \mid X_1, \vec{Y})}_{\text{LLM-Generated Response (1)}} = \underbrace{\sum_{Y} p(Y' = 2 \mid Y = 1, X_1, \vec{Y})}_{\substack{\textbf{Estimated Instance-Response}\\ \textbf{Dependent Discrepancies (3)}}} \underbrace{p(Y = 1 \mid X_1, \vec{Y})}_{\text{User-Preferred Response (2)}} . \tag{8}$$

With an accurate estimate of $\sum_{Y'} p(Y' \mid Y, X)$, the conditional likelihood $p(Y \mid X)$ can be maximised without full per-user fine-tuning.

6 Experiment

6.1 Evaluation Setup

To assess the *effectiveness* and *generalisability* of **Consistent Marginalization (CM)**, we conduct experiments on three widely used LLMs—**Chatgpt-4o-mini**, **Chatgpt-3.5**, and **Llama-8b-Instruct**—each run with two random seeds for robustness. CM is benchmarked against standard prompt and recent self-correction baselines on five diverse, real-world datasets: **StackExchange**: a multi-domain QA corpus (e.g., programming) that tests how well an LLM aligns responses in varied, user-specific contexts. **CLINC150**: 150 intent categories drawn from realistic dialogue, measuring an LLM's ability to capture subtle user preferences in high-variance settings. **BANK77**: banking-themed user queries that probe alignment performance in high-stakes, user-sensitive scenarios. **MOTE**: a multilingual dataset for evaluating CM's cross-lingual adaptability. **Massive Scenario**: 51 typologically-diverse multilingual natural language understanding dataset, highlighting CM's scalability to broad situations and linguistic coverage. For each LLM, we compare every baseline prompt method with its CM-enhanced counterpart under identical conditions—that is, *Baseline Prompt* versus CM + *Baseline Prompt* —and report results averaged over the two seeds.

Metric Dataset	ChatGPT-3.5 StackExchange(Topic)	ChatGPT-3.5 CLINC150(Intent)	ChatGPT-3.5 Banking77(Intent)	ChatGPT-3.5 MOTE(Intent)	ChatGPT-3.5 Massive(Scenario)
CotWei et al. (2022)	49.82% ± 0.19%	64.62% ± 1.63%	19.16% ± 0.14%	57.42% ± 0.40%	60.54% ± 0.24%
$CM_{3.5}$+ Cot	**54.72% ± 0.17%**	**68.09% ± 1.92%**	**31.90% ± 0.30%**	**64.91% ± 0.36%**	**68.11% ± 0.43%**
FoTBrown et al. (2020)	46.04% ± 0.01%	61.62% ± 1.16%	36.77% ± 0.44%	55.93% ± 0.23%	58.23% ± 0.45%
$CM_{3.5}$+ FoT	**51.92% ± 0.08%**	**63.53% ± 1.23%**	**45.94% ± 0.60%**	**63.94% ± 1.15%**	**66.70% ± 0.86%**
Zero-Shot	51.96% ± 0.02%	63.18% ± 1.13%	62.55% ± 0.85%	65.84% ± 0.47%	62.22% ± 0.05%
$CM_{3.5}$+Zero-Shot	**56.29% ± 0.04%**	**67.84% ± 1.70%**	**66.92% ± 1.10%**	**74.36% ± 0.73%**	**67.26% ± 0.12%**
Self-ConsistencyWang et al. (2022)	51.75% ± 0.06%	68.90% ± 0.08%	56.61% ± 0.34%	68.26% ± 0.26%	62.49% ± 0.19%
$CM_{3.5}$+Consistent	**53.96% ± 0.08%**	**69.36% ± 0.19%**	**57.42% ± 0.44%**	**75.57% ± 0.77%**	**64.63% ± 0.12%**
Self-RefineMadaan et al. (2024)	48.94% ± 0.68%	71.63% ± 1.24%	53.90% ± 2.94%	**71.88% ± 0.59%**	63.55% ± 0.02%
$CM_{3.5}$+Self-Refine	**54.09% ± 0.04%**	**75.29% ± 1.23%**	**57.87% ± 3.37%**	68.05% ± 0.29%	**68.27% ± 0.40%**
Metric Dataset	**Llama-8B Instruct StackExchange(Topic)**	**Llama-8B Instruct CLINC150(Intent)**	**Llama-8B Instruct Banking77(Intent)**	**Llama-8B Instruct MOTE(Intent)**	**Llama-8B Instruct Massive(Scenario)**
CotWei et al. (2022)	14.72% ± 0.19%	32.24% ± 0.55%	22.20% ± 0.45%	55.75% ± 0.21%	46.94% ± 0.10%
CM_{Llama}+Cot	**23.22% ± 0.02%**	**33.08% ± 0.24%**	**24.62% ± 0.19%**	**56.89% ± 0.16%**	**50.27% ± 0.24%**
FoT Brown et al. (2020)	14.61% ± 1.47%	42.84% ± 1.06%	25.07% ± 0.78%	**66.87% ± 0.84%**	54.91% ± 1.38%
CM_{Llama}+FoT	**26.56% ± 0.20%**	**43.84% ± 0.25%**	**29.00% ± 0.35%**	65.50% ± 0.93%	**56.49% ± 0.95%**
Zero-Shot	17.80% ± 0.19%	58.24% ± 0.69%	49.03% ± 0.13%	41.09% ± 1.42%	55.82% ± 0.19%
CM_{Llama}+Zero-Shot	**22.66% ± 0.09%**	**59.78% ± 0.67%**	**55.19% ± 0.45%**	**50.91% ± 1.77%**	**63.95% ± 0.57%**
Consistent Wang et al. (2022)	19.32% ± 0.12%	55.36% ± 0.11%	38.31% ± 0.26%	63.43% ± 0.55%	57.53% ± 1.09%
CM_{Llama}+Consistent	**24.76% ± 0.07%**	**55.42% ± 0.31%**	**43.34% ± 0.35%**	**65.98% ± 0.32%**	**59.95% ± 0.62%**
Self-Refine Madaan et al. (2024)	18.9% ± 0.14%	60.19% ± 0.98	48.70 ± 0.28%	42.64% ± 1.05%	55.75% ± 0.19%
CM_{Llama}+Self-Refine	**23.34% ± 0.48%**	**61.42% ± 1.23%**	**55.23% ± 0.32%**	**51.41% ± 0.93%**	**63.85% ± 0.52%**
Metric Dataset	**ChatGPT-4-o-mini StackExchange(Topic)**	**ChatGPT-4-o-mini CLINC150(Intent)**	**ChatGPT-4-o-mini Banking77(Intent)**	**ChatGPT-4-o-mini MOTE(Intent)**	**ChatGPT-4-o-mini Massive(Scenario)**
Cot Wei et al. (2022)	44.72% ± 0.19%	74.55% ± 2.73%	59.41% ± 0.50%	**69.70% ± 1.07%**	63.99% ± 0.69%
$CM_{3.5}$+Cot	**49.54% ± 0.31%**	**75.76% ± 3.22%**	**65.32% ± 1.73%**	69.25% ± 1.32%	**66.40% ± 0.38%**
FoT Brown et al. (2020)	42.81% ± 0.40%	73.14% ± 2.33%	55.87% ± 0.10%	66.23% ± 0.81%	67.49% ± 0.12%
$CM_{3.5}$+FoT	**48.09% ± 0.35%**	**74.60% ± 2.48%**	**62.74% ± 0.89%**	**67.60% ± 0.94%**	**70.03% ± 0.19%**
Zero-Shot	49.94% ± 0.36%	**83.23% ± 1.11%**	66.61% ± 1.82%	**73.79% ± 0.61%**	**72.04% ± 0.07%**
$CM_{3.5}$+Zero-Shot	**50.02% ± 0.25%**	82.70% ± 1.56%	**69.45% ± 2.30%**	73.72% ± 0.94%	71.03% ± 0.07%
Consistent Wang et al. (2022)	47.63% ± 0.37%	**81.85% ± 0.63%**	**66.08% ± 1.38%**	74.00% ± 0.32%	**70.82% ± 0.02%**
$CM_{3.5}$+Consistent	**48.19% ± 0.27%**	79.86% ± 1.53%	65.86% ± 1.30%	**79.82% ± 0.90%**	69.81% ± 0.40%
Self-RefineMadaan et al. (2024)	**51.72% ± 0.27%**	79.34% ± 0.49%	64.81% ± 1.33%	**71.93% ± 0.02%**	71.35% ± 0.29%
$CM_{3.5}$+Self-Refine	51.69% ± 0.24%	**80.21% ± 1.37%**	**68.71% ± 2.68%**	71.06% ± 0.60%	**71.72% ± 0.38%**

Table 1: Response–matching accuracy (%±STD) of several prompt methods evaluated on five domain-specific NLP datasets with three LLM back-bones: ChatGPT-3.5-Turbo, ChatGPT-4-o-mini, and Llama-8B-Instruct. For each dataset, the best score—obtained by pairing our Consistent Marginalization (CM) module with standard prompt techniques—is shown in **bold**. We report Few-Shot, Self-Consistency, Chain-of-Thought(CoT), Self-Refine, and CM variants. *Note:* $CM_{3.5}$ is learned from ChatGPT-3.5-Turbo and then applied to both ChatGPT-3.5-Turbo and ChatGPT-4-o-mini, whereas CM_{Llama} is learned and used solely on Llama-8B. The weaker gains on Chatgpt-4-o-mini highlight that an instance–response discrepancy matrix transfers poorly across model families. In contrast, it delivers substantial improvements when applied to the model on which it was estimated.

6.2 Baselines

Self-Consistency Wang et al. (2023) aims to improve the response accuracy of LLMs by considering consistently generated answers through selecting multiple and diverse paths in a few-shot chain of thought approach. The problem with this method is its dependence on multiple sources of paths from the same model; even slight changes in one source's responses can drastically impact the final responses. In addition, self-consistency only reflects the proportions of the dataset used for training the LLMS, but not the personal response preference of the user. The chain of thought method Wei et al. (2022) is a step-by-step illustration for the given query to the LLMs. Few-Shot Thought Prompting: Brown et al. (2020) uses a few relevant examples as illustrations in the prompt to aid the model in aligning the response with the user. We have also included Self-Refine Madaan et al. (2024) to show that relying on model reflection is inadequate to make a model produce persistent alignment.

Metric	StackExchange (Topic)	CLINC150 (Intent)	Banking77 (Intent)	Mtop (Intent)	Massive (Scenario)
Cot Wei et al. (2022)	14.49% ± 0.19%	**32.33% ± 0.38%**	**22.44% ± 0.10%**	55.95% ± 0.23%	47.31% ± 0.03%
$CM_{Llama}(1\%)$**+Cot**	**19.85% ± 0.02%**	32.18% ± 0.04%	22.14% ± 0.06%	**57.32% ± 0.14%**	**50.34% ± 0.24%**
FoT Brown et al. (2020)	14.73% ± 1.54%	43.02% ± 1.38%	25.45% ± 0.45%	65.50% ± 0.57%	53.30% ± 0.03%
$CM_{Llama}(1\%)$	**22.52% ± 0.38%**	**42.84% ± 0.84%**	**25.45% ± 0.39%**	**67.28% ± 0.43%**	**56.25% ± 0.17%**
Zero-Shot	18.46% ± 0.07%	**58.04% ± 0.40%**	**48.70% ± 0.45%**	40.08% ± 0.05%	55.41% ± 0.27%
$CM_{Llama}(1\%)$**+Zero-Shot**	**22.47% ± 0.10%**	58.22% ± 0.22%	48.38% ± 0.52%	**51.12% ± 0.23%**	**62.14% ± 0.34%**
Consistent Wang et al. (2022)	19.42% ± 0.02%	**55.53% ± 0.02%**	**38.05% ± 0.19%**	62.75% ± 0.41%	56.96% ± 0.13%
$CM_{Llama}(1\%)$**+Consistent**	**23.75% ± 0.31%**	54.40% ± 0.04%	37.92% ± 0.26%	**66.19% ± 0.52%**	**59.92% ± 0.20%**
Self-Refine Madaan et al. (2024)	18.94% ± 0.07%	**58.47% ± 0.38%**	**48.38% ± 0.45%**	41.36% ± 0.14%	55.35% ± 0.34%
$CM_{Llama}(1\%)$**+Self-Refine**	**22.71% ± 0.05%**	58.27% ± 0.22%	48.21% ± 0.55%	**51.03% ± 0.05%**	**62.10% ± 0.30%**

Table 2: Response–matching accuracy (%±STD) of several prompt methods evaluated on five domain-specific NLP datasets with Llama-8B-Instruct. For each method (row), the best score across datasets is shown in **bold**. *Note:* $CM_{Llama}(1\%)$ is estimated with 1% of the training sample and used solely on Llama-8B.

Table 3: Comparison between Prompt-Based Methods and Consistent Marginalization (CM) on Personalized Response Alignment Task

Method	**Objective**	**Correction Mechanism**	**Personalised Alignment Ability**	**Memory of Past Misalignment**	**External Tool**	**Limitations on Personalised Response Alignment Task**
Few-Shot Brown et al. (2020)	General task performance	None	✗ Low	✗ Implicit via reasoning paths	No	Cannot adapt to user-specific preferences or feedback
Chain of Thought (Wei et al., 2022)	Improve reasoning accuracy	Implicit via reasoning path	✗ Low	✗ None	No	No adaptation to feedback; prone to hallucinations
Self-Consistency (Wang et al., 2023)	Improve response accuracy	Majority voting over responses	✗ Low	✗ None	No	Relies on diverse paths; No user-specific guidance
Self-Refine (Madaan et al., 2024)	Iterative self-correction with Feedback	Self-generated revision loop	Medium	✗ None	Yes	Requires Many Iterative rounds of Correction. Lack of long-term Memory
Consistent Marginalization (Ours)	Personalized response alignment	Explicit memory of instance-response dependent discrepancies	✓**High**	✓ Yes	No	**No need for per-user Fine-tune; scalable and adaptive to personalised user preferences**

6.3 Experimental Result

6.3.1 Robust Gains with Just 5 % User-Preference Samples

Consistent Marginalization (CM) is both effective and adaptable. As Table 4 shows, adding CM to every plain-prompt baseline raises response-matching accuracy across all datasets on **Chatgpt-3.5** and **Llama-8b-Instruct**, and delivers notable gains on **Chatgpt-4o-mini**. **ChatGPT-3.5-Turbo.** CM improves every prompt strategy on four of the five datasets; the single dip occurs with CM+Self-Refine on MOTE. The largest boost is **+12.74 %** on Banking77 with CM+CoT, while the other datasets record balanced gains of +3–8 %. **Llama-8B-Instruct.** CM produces the strongest overall gains: 23 of 25 cases improve, 16 by at least 2 %. The highest is **+11.95 %** on StackExchange with CM+FoT; the single drop is a mild −1.37 % on MOTE with CM +FoT. **ChatGPT-4o-mini.** Because the discrepancy matrix was learned on GPT-3.5-Turbo, gains transfer slightly less, yet CM still adds **+6.87 %** on Banking 77 with CM+FoT and remains positive or neutral on most other cells. Overall, with just 5% of user-preference samples, CM consistently outperforms every plain-prompt baseline, confirming its practical value across prompts, datasets, and LLM architectures.

6.3.2 Moderate Gains with Just 1% User-Preference Samples

To quantify how many annotated preferences CM needs, we perform an ablation using **Llama-8b-Instruct** and two annotation budgets—**1**% and **5**% of the training set—across all five datasets (Table 2). **Robust gains with only 1 %.** Even at the 1 % budget, CM lifts nearly every prompt baseline. The largest jump occurs on StackExchange, where CM raises *FoT* from 14.73 % to 22.52 % (+7.79 pp) and *Consistent* from 19.42 % to 23.75 % (+4.33 pp). These results show that CM is practical in low-data settings. **Moderate gains from 1 % → 5 %.** Moving to 5 % of user-preference samples yields further, but smaller,

improvements—evidence of diminishing returns once the discrepancy matrix is well estimated. Overall, CM scales smoothly with additional data while remaining highly effective in resource-constrained regimes.

Table 4: Response Alignment Accuracy improvement (%) of Consistent Marginalization (CM) over baseline prompt methods across datasets.

Model + Method	StackExchange	CLINC150	Banking77	MOTE	Massive (Intent)
ChatGPT-3.5					
$CM_{3.5}$ +Cot	**+4.90%**	**+3.47%**	**+12.74%**	**+7.49%**	**+7.57%**
$CM_{3.5}$ +FoT	**+5.88%**	+1.91%	**+9.17%**	**+8.01%**	**+8.47%**
$CM_{3.5}$ +Zero-Shot	**+4.33%**	**+4.66%**	+4.37%	**+8.52%**	**+5.04%**
$CM_{3.5}$ +Consistent	+2.21%	+0.46%	+0.81%	**+7.31%**	+2.14%
$CM_{3.5}$ +Self-Refine	**+5.15%**	**+3.66%**	+3.97%	**-3.83%**	**+4.72%**
Llama 8B Instruct					
CM_{Llama} +Cot	**+8.50%**	+0.84%	**+2.42%**	+1.14%	**+3.33%**
CM_{Llama} +FoT	**+11.95%**	+1.00%	**+3.93%**	-1.37%	+1.58%
CM_{Llama} +Zero-Shot	**+4.86%**	**+1.54%**	**+6.16%**	**+9.82%**	**+8.13%**
CM_{Llama} +Consistent	**+5.44%**	+0.06%	**+5.03%**	**+2.55%**	**+2.42%**
CM_{Llama} +Self-Refine	**+4.44%**	**+1.23%**	**+6.53%**	**+8.77%**	**+8.10%**
ChatGPT-4o-mini					
$CM_{3.5}$ +Cot	**+4.82%**	+1.21%	**+5.91%**	-0.45%	+2.41%
$CM_{3.5}$ +FoT	**+5.28%**	+1.46%	**+6.87%**	+1.37%	+2.54%
$CM_{3.5}$ +Zero-Shot	+0.08%	-0.53%	+2.84%	-0.07%	-1.01%
$CM_{3.5}$ +Consistent	+0.56%	**-1.99%**	-0.22%	**+5.82%**	-1.01%
$CM_{3.5}$ +Self-Refine	-0.03%	+0.87%	+3.90%	-0.87%	+0.37%

Additional LLM: ChatGPT-4 Turbo. To test the cross-model consistency of CM, we transfer the instance–response discrepancies estimated on ChatGPT-3.5-Turbo to **ChatGPT-4 Turbo**. As Table 5 shows, this transfer still lifts the *Zero-Shot Prompt* baseline by **3.5 %** in response alignment ratio, showing that $CM_{3.5}$ remains useful even on a stronger backbone. However, the absolute gain is smaller than on ChatGPT-3.5-Turbo. We attribute the drop to model architecture and parameter difference : the larger the gap between the source model (where the discrepancies were learned) and the target model, the less precisely those discrepancies characterise the new model's misalignment. This observation indicates that the effectiveness of a instance response dependent discrepancy decays as the underlying LLM family shift farther from the one on which it was estimated.

Method	Ratio (%)
Zero-Shot (GPT-3.5)	62.99
$CM_{3.5}$+Zero-Shot	**67.35**
Zero-Shot (GPT-4 Turbo)	61.98
$CM_{3.5}$+Zero-Shot	**64.48**

Table 5: Cross-LLMs Consistency of CM

7 Conclusion

We have introduced Consistent Marginalization(CM), a paradigm that enables large language models to deliver genuinely personalised responses by explicitly modelling *instance-response–dependent* discrepancies. CM's learning objective stores each misalignment between the model's draft and the user-preferred answer, then recalls this memory to "unlearn" past errors and adapt future outputs. With only a small set of annotated preference examples—no per-user fine-tuning—CM detects and corrects these discrepancies, steadily steering the LLM toward the user's desired style. Experiments across multiple LLM backbones and five diverse, large-scale datasets show consistent gains in response alignment, confirming CM's practicality and robustness in data-constrained settings.

Broader Impact Statement

To the best of our knowledge, our research does not introduce any negative societal or ethical consequences.

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8 Appendix

8.1 Table of Notations

Table 6: Summary of Notations Used in the Paper

Symbol	Description
X	User query or input instance
Y	User-preferred (true) response
Y'	LLM-generated response (possibly misaligned)
$\bar{Y}$	Refined response generated by LLM using CM's personalised memory bank
$\vec{Y}$	Candidate response set for input X
$\vec{Y}_{\text{Query}}$	Initial candidate response matrix (e.g., all 1's)
$\vec{Y}_{\text{Updated}}$	Updated candidate response set via CM memory
$\vec{Y}_{\text{Refined}}$	Final refined candidate set passed to LLM
Y_G	One-hot ground-truth labels for user-preference samples
Z	Prompting strategy (latent variable)
Z^*	Optimal or fixed prompt (assumed given)
$p(Y \mid X, Z)$	Probability of generating Y under prompt Z
$p(Y' \mid Y, X)$	Instance–response dependent discrepancy distribution
$M(X)$	Deterministic discrepancy (transition) matrix
D_{User}	User-preference dataset (annotated samples)
D_{Large}	Large unlabeled dataset
s	Number of annotated (user-preference) samples
n	Total number of training samples
c, K	Number of possible response classes
G	The LLM model used to generate responses

8.2 Comprehensive comparison table showing the performance differences between 1% and 5% user-preference samples across all methods and datasets

Dataset	Method	1% Acc	5% Acc	Improvements
StackExchange	Cot	14.49	14.72	+0.23
	CM+Cot	19.85	23.22	**+3.37**
	FoT	14.73	14.61	-0.12
	CM+FoT	22.52	26.56	**+4.04**
	Consistent	19.42	19.32	-0.10
	CM+Consistent	23.75	24.76	**+1.01**
CLINC150	Cot	32.33	32.24	-0.09
	CM+Cot	32.18	33.08	+0.90
	Zero-Shot	58.04	58.24	+0.20
	CM+Zero-Shot	58.22	59.78	**+1.56**
	Self-Refine	58.47	60.19	**+1.72**
	CM+Self-Refine	58.27	61.42	**+3.15**
Banking77	Cot	22.44	22.20	-0.24
	CM+Cot	22.14	24.62	**+2.48**
	FoT	25.45	25.07	-0.38
	CM+FoT	25.45	29.00	**+3.55**
	Zero-Shot	48.70	49.03	+0.33
	CM+Zero-Shot	48.38	55.19	**+6.81**
	CM+Self-Refine	48.21	55.23	**+7.02**
Mtop	Cot	55.95	55.75	-0.20
	CM+Cot	57.32	56.89	-0.43
	FoT	65.50	66.87	**+1.37**
	CM+FoT	67.28	65.50	-1.78
	Consistent	62.75	63.43	+0.68
	CM+Consistent	66.19	65.98	-0.21
Massive	Cot	47.31	46.94	-0.37
	CM+Cot	50.34	50.27	-0.07
	FoT	53.30	54.91	**+1.61**
	CM+FoT	56.25	56.49	+0.24
	Zero-Shot	55.41	55.82	+0.41
	CM+Zero-Shot	62.14	63.95	**+1.81**
	CM+Self-Refine	62.10	63.85	**+1.75**

Table 7: Accuracy comparison between 1% and 5% user-preference samples. Bold indicates improvements >1%.