

PROMPT REINFORCING FOR LONG-TERM PLANNING OF LARGE LANGUAGE MODELS

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ABSTRACT

Large language models (LLMs) have achieved remarkable success in a wide range of natural language processing tasks and can be adapted through prompting. However, they remain suboptimal in multi-turn interactions, often relying on incorrect early assumptions and failing to track user goals over time, which makes such tasks particularly challenging. Prior works in dialogue systems have shown that long-term planning is essential for handling interactive tasks. In this work, we propose a prompt optimisation framework inspired by reinforcement learning, which enables such planning to take place by only modifying the task instruction prompt of the LLM-based agent. By generating turn-by-turn feedback and leveraging experience replay for prompt rewriting, our proposed method shows significant improvement in multi-turn tasks such as text-to-SQL and task-oriented dialogue. Moreover, it generalises across different LLM-based agents and can leverage diverse LLMs as meta-prompting agents. This warrants future research in reinforcement learning-inspired parameter-free optimisation methods.

1 INTRODUCTION

Large language models (LLMs) have shown an extraordinary ability to perform a wide range of tasks, from generating images in various styles to writing code in different programming languages for diverse purposes. LLMs are typically post-trained using reinforcement learning from human feedback (RLHF) (Ouyang et al., 2022), where they receive single-turn rewards for individual responses rather than rewards reflecting the quality of an entire multi-turn conversation. This limits their effectiveness in interactions where tasks are underspecified and clarified over time, often leading to early mistakes, incorrect assumptions, and cascading failures (Laban et al., 2025). On the other hand, prior work in dialogue systems demonstrates that long-term planning is vital for interactive tasks, making it essential for LLMs (Young, 2002; Young et al., 2013).

Directly optimising LLMs could improve their ability to plan across multiple turns, e.g., supervised fine-tuning with low-rank adaptation (Hu et al., 2022), direct preference optimisation (Feng et al., 2025b), continuous prompting (Lester et al., 2021; Qin & Eisner, 2021; Li & Liang, 2021; Liu et al., 2023), or reinforcement learning with dialogue-level rewards (Feng et al., 2025a); however, these approaches are often impractical for real-time updates due to high computational costs, especially with limited local resources, and are incompatible with API-only LLMs.

Gradient-free methods, such as instruction-feedback-refine pipelines (Peng et al., 2023; Shinn et al., 2023; Yao et al., 2023; Elizabeth et al., 2025), avoid parameter updates but rely on frequent API calls during inference, leading to inefficiency. Meta-prompting and existing prompt optimisation techniques focus on input-output learning without explicitly modelling long-term planning (Yang et al., 2024a; Tang et al., 2025; Pryzant et al., 2023; Yuksekgonul et al., 2025).

To address these limitations, we propose Reinforced Prompt Optimisation (RPO). The structure of RPO is shown in Figure 1. This meta-prompting approach enhances the long-term planning ability of LLMs by iteratively refining an initial prompt based on natural language feedback, where the initial prompt can be crafted by experts or generated from a corpus via meta-prompting (Zhou et al., 2023; Pryzant et al., 2023; Ye et al., 2024).

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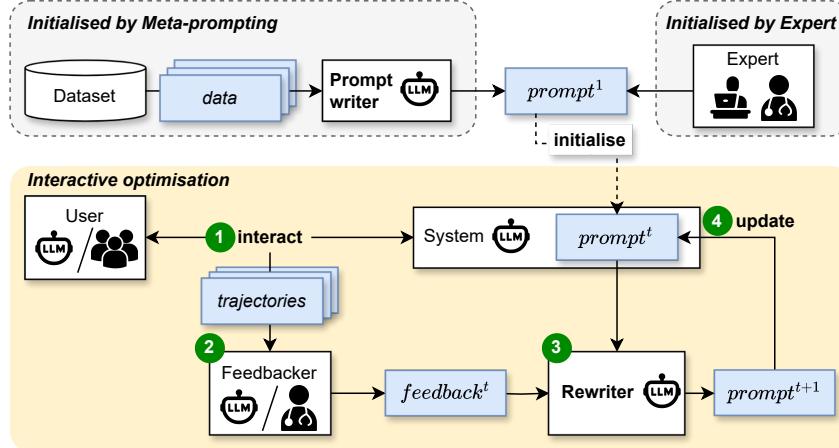


Figure 1: The structure of Reinforced Prompt Optimisation (RPO). The initial $prompt^1$ can be generated by LLMs or written by experts. In interactive optimisation, the system will first interact with the environment, e.g., simulated or real users. The feedbacker, e.g., human experts or LLMs, will provide textual feedback based on trajectories. The rewriter generates a new prompt based on the original prompt and the textual feedback to update the system’s original prompt. One cycle of interactive optimisation is called an epoch, and we use *superscripts* to denote the epoch number.

In RPO, an LLM-based system interacts with an environment, such as real or simulated users, in tasks like information seeking or medical QA. A feedbacker, either a human or an LLM, provides turn-level textual feedback inspired by temporal difference (TD) error. As shown in the right part of Figure 2, for each turn t_i , the LLM-generated feedback includes: (1) predicted user emotion in the next turn elicited by the system response a_i , (2) a forecast of dialogue success or failure, and (3) suggestions based on the subdialogue $t_{1:i}$. These are then aggregated into dialogue-level feedback.

A separate LLM-based rewriter refines the prompt based on the feedback and the previous prompt. Experience replay is applied by leveraging feedback–prompt pairs from both the current and past iterations. The updated prompt is used in future interactions. More details can be found in Section 3. Inspired by these well-studied reinforcement learning concepts, the goal of RPO is to effectively strengthen the system agent’s long-term planning ability and overall task success.

Our contributions are as follows:

- We propose Reinforced Prompt Optimisation (RPO), a meta-prompting framework that improves LLMs’ long-term planning in multi-turn tasks by iteratively updating prompts based on natural language feedback.
- We explore leveraging the concept of temporal difference (TD) error in the LLM-based feedback generation and experience replay in rewriting, enabling efficient and lower-variance prompt optimisation.
- Our method can leverage external expert reward signals without revealing the prompt of the LLM-based system and is flexible with respect to the choice of LLM backbones for the system or meta-prompting agent.

2 RELATED WORK

Gradient-based optimisation for LLMs For high parameter counts, training or fine-tuning an entire large language model is infeasible since it requires a huge amount of computational resources. As a result, parameter-efficient fine-tuning, such as training only part of the model or freezing the model and training an adapter, is widely used to refine LLMs (Hu et al., 2022; 2023; Lialin et al., 2023). On the other hand, continuous prompting, e.g., prefix-tuning and soft-prompting, is also popular to adapt LLMs to specific tasks or improve their performance (Lester et al., 2021; Qin & Eisner, 2021; Li & Liang, 2021; Liu et al., 2023). By updating inputs of every attention layer (Li

& Liang, 2021), or task-related vectors (Lester et al., 2021), these methods can achieve comparable performance to full fine-tuning across various model sizes and tasks (Liu et al., 2022). Although these methods can improve LLMs effectively, they do not apply to API-access-only LLMs, and such training processes cannot be carried out in real-time.

Self-feedback To improve the performance of text-based prompts, various prompting styles are proposed, e.g., Chain-of-Thought (Wei et al., 2022) or ReAct (Yao et al., 2023). These prompting methods encourage LLMs to reason before taking action or generating responses, which leads to better performance. However, optimising the prompt for better performance by manual trial and error is inefficient. Instead, self-feedback methods are introduced to refine the LLMs’ response, e.g., LLM-augmenter generates feedback by itself and leverages external knowledge to rewrite its response (Peng et al., 2023), and Reflexion summarises previous interactions with the environment as ‘reflections’ to improve the model’s response (Shinn et al., 2023).

While this demonstrates the ability of LLMs for self-correction, these self-feedback methods rely on frequent API calls since their original prompt is not optimal. As a result, the computation cost and latency during inference are not negligible.

Prompt optimisation Meta-prompting methods are widely used to generate a prompt without human editing. The automatic prompt engineer (APE) method leverages an LLM, which is instructed to generate an initial prompt and selects the prompt with the best performance on the target task (Zhou et al., 2023). Automatic prompt optimisation (APO) further employs a self-feedback module to provide textual feedback, which gives suggestions on how to edit the old prompt (Pryzant et al., 2023). Ye et al. (2024) propose a meta-prompt LLM to edit the original prompt step-by-step. Kong et al. (2024) and Cheng et al. (2024) train a sequence-to-sequence model for prompt rewriting by reinforcement learning and preference data, respectively. Yang et al. (2024a) propose optimisation by prompting (OPRO), which leverages LLMs to rewrite the original prompt based on a corresponding performance score. To leverage experience, Zhang et al. (2023) model LLMs as semi-parametric RL agents with memory storing task data, actions, and Q -value estimates for few-shot in-context learning. Zhang et al. (2024) propose Agent-Pro, which constructs policy-level reflections according to the numerical feedback from the environment and improves its policy incrementally. Tang et al. (2025) introduce the Gradient-inspired LLM-based Prompt Optimizer (GPO), which updates the prompt iteratively based on numerical feedback and controls the edit distance through a cosine-based decay strategy. TextGrad generates textual feedback based on the user input and system output for prompt rewriting (Yuksekgonul et al., 2025). Although these methods demonstrate promising performance in generating or improving prompts, they focus on single-turn tasks. Our approach addresses multi-turn interactions, where prompts are updated with temporally grounded feedback to enhance long-term planning ability.

Learning ability of LLMs via prompting Although transformers are universal approximators (Yun et al., 2020) and in-context learning in LLMs can be viewed as implicit fine-tuning (Dai et al., 2023), the following remain open questions: Can we prompt LLMs for arbitrary tasks, and what are the limitations of in-context learning?

Petrov et al. (2024) highlight the limitations of context-based fine-tuning methods, e.g., in-context learning, prompting, and prefix tuning, for new task learning in transformers. Specifically, transformers struggle to acquire new tasks solely through prompting, as prompts cannot change the model’s attention patterns. Instead, they can only bias the output of the attention layers in a fixed direction and elicit skills learned through pre-training. In other words, only models with billions of parameters trained on vast, diverse datasets are capable of in-context learning, adapting to new tasks through examples or instructions without modifying their underlying weights. Therefore, we focus on fundamental models large enough to demonstrate their in-context learning ability, to investigate reinforcement prompt optimisation, which is fully composed of in-context learning with LLMs.

3 REINFORCED PROMPT OPTIMISATION

Inspired by the gradient-based optimisation and reinforcement learning algorithms, where a model is initialised from pretraining and then further updated by on-policy learning based on interactions with the environment, we propose the Reinforced Prompt Optimisation (RPO) method (as shown in

Figure 1). The initial instruction can be generated by a prompt writer LLM_P such as the automatic prompt engineer (APE) (Zhou et al., 2023) (the upper left part of Figure 1) or written by human experts (the upper right part of Figure 1).

In the interactive optimisation (the lower part of Figure 1), the **system** will interact with the environment, e.g., human users or simulated users, and generate several multi-turn *trajectories*, which, for example, can be task-oriented dialogue or medical question-answering. Then the **feedbacker**, which can be a language model LLM_F or human experts, will provide textual feedback to guide the optimisation direction for the **rewriter** LLM_R , which will generate a new prompt to improve the system’s performance based on the feedback and original prompt.

We emphasise that although our method shares a feedback–rewrite structure similar to self-refine approaches, the key difference lies in the target of refinement. Self-refine methods polish the agent’s output, whereas our method updates its instruction. In other words, we treat the system’s instruction as a textual parameter to be modified, which reduces serving costs and latency by lessening the need for a multi-agent-style feedback and rewriting pipeline.

3.1 FEEDBACK GENERATION

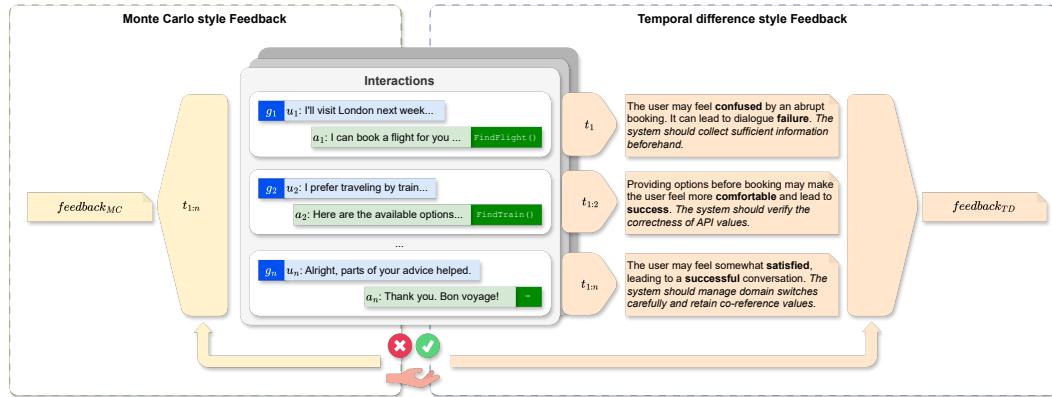


Figure 2: Workflow of feedback generation by an LLM. The Monte Carlo–style feedback (left) is generated after the entire interaction is completed, whereas the Temporal Difference–style feedback (right) consists of turn-level sub-feedback. Each sub-feedback includes a prediction of next-turn user satisfaction, a prediction of goal success, and an actionable suggestion.

As shown in Figure 2, we consider two approaches for generating feedback via LLMs: Monte Carlo (MC)-style feedback and Temporal Difference (TD)-style feedback generation.

The **MC-style feedback** is produced only after the entire dialogue trajectory ($t_{1:n}$) has been completed (the prompt of the MC-style feedbacker is shown in Figure 9):

$$feedback_{MC} = LLM_F(t_{1:n}) \quad (1)$$

This approach is commonly used in single-turn tasks such as sequence classification, named-entity recognition, or one-turn question answering (Pryzant et al., 2023; Ye et al., 2024; Wang et al., 2024; Tang et al., 2025; Yuksekgonul et al., 2025). It typically yields prompt modification suggestions based on a global success or failure signal. While this captures the overall quality of the interaction, it collapses the inherently multi-turn nature of real-world interactions into a single outcome.

In contrast, **TD-style feedback** incorporates turn-level evaluations:

$$feedback_{TD,j} = LLM_F(t_1, feedback_{TD,1}, t_2, feedback_{TD,2}, \dots, t_j), \quad (2)$$

where $feedback_{TD,j}$ is the turn-level feedback at turn j . All turn-level feedback, $feedback_{TD,1:j}$, will be summarised by LLM_F into a final $feedback_{TD}$ afterwards (details of the prompt are shown in Figure 10). Rather than waiting until the dialogue ends, the feedbacker provides incremental assessments at each turn, including the prediction of user sentiment and expected dialogue success, along with actionable suggestions.

In other words, TD-style feedback treats the immediate user response as a short-term reward (Ghazarian et al., 2022), while also estimating long-term outcomes such as task success. This idea can be formalised through the *TD error*, which balances short-term reward and long-term estimation:

$$\delta_t = r_t + \gamma V(s_{t+1}) - V(s_t) \quad (3)$$

where r_t corresponds to the short-term reward (e.g., user sentiment after the current turn), $V(s_t)$ is approximated by the previous turn-level feedback, and $V(s_{t+1})$ represents the estimated long-term value of continuing the dialogue toward successful task completion. This dual perspective enables the system to refine both local decision-making at the turn level and global trajectory planning across the full interaction.

3.2 APPLYING FEEDBACK TO THE PROMPT

Unlike gradient-based optimisation, where gradients can be added or subtracted from model parameters, incorporating textual feedback into prompts is non-trivial. One cannot concatenate or remove arbitrary text from the original prompt without risking incoherence or loss of functionality. To address this, we introduce a basic *rewriter LLM_R* to apply textual feedback on the original prompt:

$$prompt^{i+1} = \text{LLM}_R(prompt^i, feedback^i), \quad (4)$$

where i denotes the epoch index. Its instruction is shown in Figure 7.

Inspired by experience **replay** in reinforcement learning (Andrychowicz et al., 2017), the rewriter can leverage not only the prompt and feedback from the current epoch, but also those from previous epochs (its instruction is shown in Figure 8):

$$prompt^{i+1} = \text{LLM}_R(prompt^i, feedback^i, prompt^{i-1}, feedback^{i-1}, \dots, prompt^1, feedback^1). \quad (5)$$

Reinforced Prompt Optimisation (RPO) alleviates the need for task-specific manual prompt engineering by automating prompt creation and refinement entirely through LLMs. The feedback signal may originate from either simulated environments or human users. Importantly, while the feedbacker and rewriter themselves are LLMs that require prompts, these prompts are task-independent and need to be specified only once. Optimising the prompts of these meta-prompting agents lies beyond the scope of this work and is left for future research.

4 EXPERIMENT SETTINGS

In this study, we focus on iterative meta-prompting by leveraging textual feedback from the environment. We conduct experiments on three challenging human–machine interaction tasks that require multiple turns: Text-to-SQL, Task-oriented Dialogue, and Medical Question-answering (Section 4.1). An overview is shown in Figure 3. Our meta-prompting components are task-agnostic (Section 4.2). They are designed to optimise the prompt of interactive LLM-based systems (Section 4.3). Furthermore, to assess how different prompts affect system performance, all prompts are in a zero-shot in-context learning fashion¹, consisting only of task descriptions without examples.

4.1 TASKS

Text-to-SQL Laban et al. (2025) proposed 6 tasks to study the performance drop of LLMs from fully-specified user queries to multi-turn interactions. The multi-turn, sharded instruction (e.g., Shard 1 conveys the high-level intent, and subsequent shards provide incremental clarifications) is partitioned based on the single-turn, fully-specified instruction from the original dataset. The largest decline occurs in the Text-to-SQL task, which we therefore select to study under different prompt optimisation methods, using instructions and databases from the Spider dataset (Yu et al., 2018).

In this task, the system agent receives a database schema at the start of the interaction and generates SQL queries from user queries in natural language. We evaluate both closed-source LLMs (GPT-4o mini, Gemini-2.0-flash) and open-source LLMs (Llama-3.1-8B, Llama-3.1-70B, Llama-4-scout) to

¹Following Brown et al. (2020), this is in-context learning since task descriptions are given as context, but also zero-shot because no demonstrations are included.

	Objective ← → Subjective		
Task	Text-to-SQL	Task-oriented dialogue	Medical Question-Answering
User instruction	Let's find unpopular museum focus on museums that have not had any visitors at all return the name of the museum	You are looking for a place to stay, the hotel should be in the cheap price range and in the city centre . You also need to find a restaurant nearby.	I only have cough as a symptom. Please recommend Chinese medicine or a prescription .
Dataset	Lost_in_conversation based on Spider	MultiWOZ	Huatuo-26M & ShenNong-TCM
Evaluation	Database result exact match	Goal success	Safety, Professionalism, and Fluency by human expert

Figure 3: The summary of our experiment tasks.

test whether prompt optimisation generalises across different LLMs. The agent is optimised in the multi-sharded environment and evaluated by *functional accuracy*, requiring generated SQL queries to exactly match the reference outputs across all databases.

Task-oriented Dialogue To evaluate on a more realistic scenario, we conduct experiments on MultiWOZ 2.1 (Budzianowski et al., 2018; Eric et al., 2020), containing 10k human-to-human conversations on information-seeking, recommendations, and reservations across multiple domains. In this work, we focus on the attraction, hotel, restaurant, and train domains, under the ConvLab-3 framework (Zhu et al., 2023). Each user goal of the simulated user is a plain-text description of requirements, e.g., “*You are looking for a place to stay, the hotel should be in the cheap price range and in the city centre. You also need to find a restaurant nearby.*”

The system agent is FnCTOD (Li et al., 2024), built with GPT-4o mini. In comparison to the standard, single-stage LLM-based system, FnCTOD consists of two parts: dialogue state tracking as a function call to access external databases, and response generation based on function call results. Both prompts are subject to optimisation. The performance of the system is measured by *success rate*, i.e., whether the recommended entities satisfy user goals and all the requested information is fulfilled, based on a rule-based evaluator in ConvLab-3.

Medical Question-Answering To evaluate our system in a more human-centred setting and how well prompting can improve the model’s performance in a domain that is not common in the pre-training data, we use two medical question-answering datasets: Huatuo-26M (Wang et al., 2025) and ShenNong-TCM (Wei Zhu & Wang, 2023). The questions in Huatuo-26M and ShenNong-TCM are collected from the internet, e.g., encyclopedias, books, literature, and web corpus, or generated by an LLM based on a traditional Chinese medicine entity graph in Huatuo-26M and ShenNong-TCM, respectively. Simulated users act based on descriptions in plain text, related to general medicine or traditional Chinese medicine, e.g., “我只有咳嗽這一個症狀，請幫我推薦中藥或者方劑。(I only have cough as a symptom. Please recommend Chinese medicine or a prescription.)”.

The system agent is built with GPT-4o mini, interacting with users in single-turn or multi-turn settings. It does not access external knowledge bases but relies solely on pre-training knowledge. At each epoch, an expert with degrees in general medicine and traditional Chinese medicine provides feedback on 10 interactions. For evaluation, three different experts compare 2 systems on 30 interaction pairs in general medicine and 30 in traditional Chinese medicine per expert (90 per domain in total), based on safety, professionalism, and fluency, following the setting in Yang et al. (2024b).

4.2 META-PROMPTING COMPONENTS

In the interactive optimisation phase, the feedbacker LLM_F and rewriter LLM_R are built with closed-source LLMs, e.g. GPT-4o mini (OpenAI et al., 2024) and Gemini-2.0-flash (Gemini Team et al., 2024), or open-source LLMs, e.g. Llama-3.1-8B, Llama-3.1-70B (Grattafiori et al., 2024), and Llama-4-scout (MetaAI, 2025). More detail is shown in Table 3. Across different tasks, the prompts of LLM_F and LLM_R remain fixed, highlighting the task-independent role of these components.

4.3 OPTIMISATION AND EVALUATION

We start by collecting interactions using the initial prompt and user instructions sampled from the training set. The feedbacker receives 10 interactions, since the context length of the LLM-based feedbacker is limited, and to efficiently incorporate human expert feedback. At each epoch, the rewriter generates 2 new prompts based on the previous prompt and the feedback. New interactions are collected with each candidate prompt, and the one with the highest score on the validation set (based on automatic metrics or human experts, depending on the task) is chosen for the next iteration.

Baselines In our experiments, we compare three prompt optimisation methods. *Automatic Prompt Optimisation (APO)* uses the user input, system output, and label to generate feedback (Pryzant et al., 2023). For multi-turn interactions, golden labels are infeasible since multiple solution paths exist; thus, we use a binary success/failure label. *Gradient-inspired Prompt Optimizer (GPO)* iteratively updates prompts using numerical feedback, e.g., functional accuracy for Text-to-SQL, task success for dialogue (Tang et al., 2025). *MC-style (TextGrad)* (Yuksekgonul et al., 2025) processes the entire conversation and generates textual feedback, as mentioned in Section 3.1.

5 RESULTS AND DISCUSSION

5.1 ROBUSTNESS AND GENERALISABILITY

System agents as different LLMs Table 1 shows the results of optimising system agents built on five LLM backbones for the text-to-SQL task. Prompt optimisation methods aim to improve system agents in the multi-sharded setting, i.e., the user only reveals part of the information in one turn. For comparison, Oracle_{Full}, a single-turn setting where the user query is fully specified at once, is taken as an upper bound. The performance gap between Baseline_{Sharded} and Oracle_{Full} (average 0.333 vs. 0.743) highlights the difficulty LLMs face in handling multi-turn interactive tasks.

RPO_{TD} outperforms prior approaches when the system agent is built with Gemini-2.0-flash, Llama-4-scout, and Llama-3.1-70B. In contrast, RPO_{TD+replay} achieves the best overall performance, with an average score of 0.477 (+54.2% over Baseline_{Sharded}). Llama-3.1-8B benefits the most, since its performance optimised by RPO_{TD+replay} (0.467) nearly matches the oracle fully-specified setting (0.505). The consistent improvements across closed-source (GPT-4o-mini, Gemini-2.0-flash) and open-source (Llama variants) models demonstrate the robustness of our approach and the effectiveness of combining temporal-difference style feedback with replay.

However, despite substantial gains over the sharded baseline, a gap to the baseline with the fully-specified user query (average 0.477 vs. 0.743) underscores that prompt optimisation can mitigate, but not fully eliminate, the degradation caused by multi-turn interactions.

Table 1: Functional accuracy of Text-to-SQL system agents built on five LLMs optimised with various methods. Oracle_{Full}: An oracle baseline in a single-turn setting with fully-specified user queries. The final two columns show the average score (Mean) and the relative improvement ($\Delta\%$) over the Baseline_{Sharded} across various LLMs. Best scores in the multi-turn setting are **bolded**.

Method	LLM of the system agent					Mean	$\Delta\%$
	GPT	Gemini	Llama-4	Llama-8B	Llama-70B		
Baseline _{Sharded} (Laban et al., 2025)	0.402	0.514	0.206	0.224	0.318	0.333	-
APO (Pryzant et al., 2023)	0.374	0.523	0.318	0.290	0.336	0.368	16.9
GPO (Tang et al., 2025)	0.458	0.523	0.299	0.290	0.308	0.376	17.5
MC-style (Yuksekgonul et al., 2025)	0.459	0.551	0.250	0.346	0.332	0.388	20.4
RPO _{TD} (ours)	0.439	0.561	0.336	0.318	0.383	0.408	28.9
RPO _{TD+replay} (ours)	0.528	0.607	0.383	0.467	0.402	0.477	54.2
Oracle _{Full} (Laban et al., 2025)	0.893	0.841	0.729	0.505	0.748	0.743	140.2

Prompt optimisation with different LLMs Table 2 reports the success rates of FnCTOD (Li et al., 2024) when optimised by different prompt optimisation methods across five LLM backbones.

The baseline system achieves a success rate of 0.420, while all optimisation methods substantially improve performance. Among prior approaches, MC-style feedback yields the strongest results with a mean success rate of 0.565 (+34.4% over baseline), slightly outperforming APO and GPO. Our proposed methods consistently surpass these baselines. In particular, RPO_{TD} achieves a mean score of 0.575 (+37.0%), demonstrating the advantage of trajectory-driven optimisation. When combined with the rewriter with experience replay, RPO_{TD+replay} delivers the best performance across all LLMs, reaching an average success rate of 0.619, corresponding to a relative improvement of 47.3%. The gains are consistent across all five LLMs, confirming that our approach is robust and generalisable, independent of the underlying model of the meta-prompting agents.

Table 2: The success rate of the task-oriented dialogue system, FnCTOD (Li et al., 2024), improved by various prompt optimisation methods leveraging 5 different LLMs. The initial success rate of FnCTOD is 0.420. Best scores are **bolded**.

Method	LLM of the meta-prompting agent					Mean	$\Delta\%$
	GPT	Gemini	Llama-4	Llama-8B	Llama-70B		
APO (Pryzant et al., 2023)	0.540	0.560	0.540	0.560	0.560	0.552	31.4
GPO (Tang et al., 2025)	0.579	0.541	0.571	0.554	0.526	0.554	32.0
MC-style (Yuksekgonul et al., 2025)	0.567	0.549	0.575	0.560	0.572	0.565	34.4
RPO _{TD} (ours)	0.578	0.562	0.586	0.594	0.556	0.575	37.0
RPO _{TD+replay} (ours)	0.625	0.622	0.618	0.622	0.606	0.619	47.3

5.2 EFFECT OF DIFFERENT STYLES AND INPUT SIGNALS OF TEXTUAL-BASED FEEDBACKER

The training curves of FnCTOD optimised by the methods of MC-style, TD-style, and TD-style+replay with Gemini-2.0-flash are shown in Figure 4a (See results with other LLMs in Figure 6). Similar to the behaviour in traditional RL optimisation, MC-style exhibits higher variance during the early stages of training, whereas TD-style is more stable and converges faster. With further training, their final performances become comparable. In contrast, incorporating experience replay into the rewriter yields more stable training and achieves the best overall performance.

We conduct a further ablation study on the impact of different information as input to the feedbacker (as shown in Figure 4b). The *basic* setting passes the dialogue in pure text. The *subjective* setting includes the user goal, and the *believe* setting adds the API call in comparison to the *basic* setting, respectively. The *full* setting is our proposed TD-style+replay, including both the user goal and the system API call.

Both the user goal and the API call are essential for optimal performance. While the user goal can be inferred from the user’s utterances and the correctness of an API call is reflected in the system’s response, providing these signals explicitly yields significant gains. The reason is that the correctness of API calls is the main challenge in task-oriented dialogue: an incorrect selection of a function indicates a misunderstanding of the user’s intent, and wrong argument values reflect

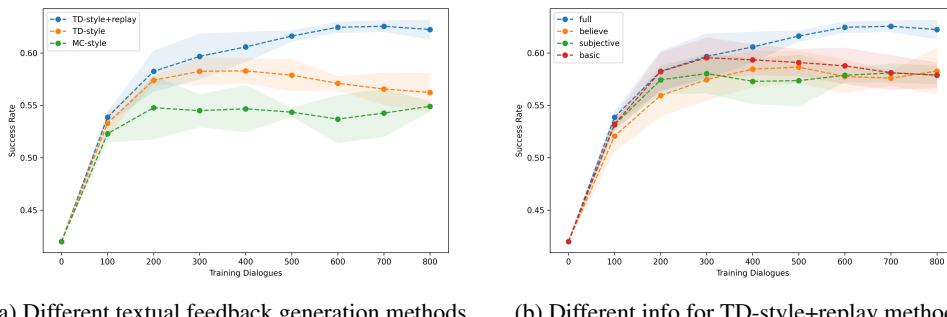


Figure 4: The training curves of different optimisation methods. Each setting is trained on 4 seeds and evaluated on 100 dialogues. The line is the average success and the shadow is the standard error.

errors in dialogue state tracking, both of which can cause the conversation to fail. An example of the prompts of FnCTOD before and after optimised by RPO_{TD+replay} can be found in Figure 11 and Figure 12, respectively.

5.3 PROMPTING LIMITATIONS ON UNDERREPRESENTED TOPICS IN LLMs

We compare our method against three systems: a standard system, built with GPT-4o mini with the initial prompt, a standard system updated via GPO, and HuatuoGPT-II (Chen et al., 2024), a large language model which is fully fine-tuned on medical data and demonstrates the state-of-the-art performance on Chinese medicine benchmarks. In other words, except HuatuoGPT-II, a fully fine-tuned 7B model, all systems are built with GPT-4o mini by prompting.

In general medicine, our method consistently outperforms the fully fine-tuned HuatuoGPT-II with an 86.7% win rate and is preferred over other prompting-based baselines. On the other hand, traditional Chinese medicine is more challenging. For example, our system’s preference rate drops by 41% compared to Huatuo when transitioning from general medicine to traditional Chinese medicine. However, despite this drop in preference, our proposed method is still favoured in general.

This observation is aligned with the findings by Petrov et al. (2024). Our method performs better in general medicine because the skills present in the pre-training data of LLMs can be elicited by prompting. However, tasks that are unseen or underrepresented in pre-training data are hard to learn through prompting. How to properly leverage external knowledge to improve the performance on unseen or under-represented tasks is an important future work.



(a) Result on general medicine.

(b) Results on traditional Chinese medicine.

Figure 5: Overall preference between our method and a standard system (Standard), GPO, and HuatuoGPT-II (Huatuo) on the medical question-answering task. The overall recommendation by human experts is based on safety, professionalism, and fluency.

6 CONCLUSIONS

We proposed a robust framework for interactive prompt optimisation that can effectively optimise system agents built on diverse LLM backbones and system structures, from standard input–output agents in text-to-SQL and medical QA to multi-stage agents in task-oriented dialogue accessing external knowledge sources. In addition, it is flexible to the choice of LLM used for generating feedback and rewriting, as it works effectively with both closed-source LLMs (GPT-4o mini and Gemini-2.0-flash) and open-source LLMs (Llama variants). Turn-level feedback enriched with user status and API details, together with experience replay in rewriting, proved highly effective for stabilising and enhancing optimisation in multi-turn tasks.

By using the optimised prompt, the system can minimise the need for extensive self-feedback loops, reducing computational overhead and API call frequency during inference. Although the performance optimised by our method still falls short of fully specified settings and unseen tasks remain difficult to optimise purely by prompting, our reinforcement learning-inspired method offers a stable, practical, and efficient approach for automatic prompt optimisation to reduce the challenges of unspecified multi-turn interactions, which could be valuable for future LLM research.

ETHIC STATEMENT

This work uses open-source datasets, such as Spider, MultiWOZ, Huatuo-26M, and ShenNong-TCM. The MultiWOZ dataset is widely used in research on task-oriented dialogue. The Huatuo-26M dataset is collected from publicly accessible data without personal information and is available to academic researchers. The ShenNong-TCM dataset is generated by GPT-3.5 based on a traditional Chinese medicine knowledge graph. As a result, these datasets should not be regarded as controversial. All interactions are generated by LLMs, which may inevitably include hallucinations or incorrect information. Human evaluators are also fully aware that they are reading interactions generated by LLMs. We use LLMs to assist with paper writing by handling language-level tasks such as grammar checking and revision.

REPRODUCIBILITY STATEMENT

The datasets used in this work are all open-sourced. The details of the model version and the access platform are listed in Appendix A. Our code repo will be released when this work is published.

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A MODEL LIST

The LLMs used in our experiment are listed in Table 3.

Table 3: Specific model versions used in our experiments.

Short Form	Name	Version	Access Provider
GPT	GPT-4o mini	gpt-4o-mini-2024-07-18	OpenAI
Gemini	Gemini-2.0-flash	gemini-2.0-flash-001	VertexAI
Llama-4	Llama-4-scout-17B-16E	llama-4-scout-17b-16e-instruct-maas	VertexAI
Llama-8B	Llama-3.1-8B	N/A	VertexAI
Llama-70B	Llama-3.1-70B	N/A	VertexAI

B CONVERAGE ANALYSIS

The training curve of prompt optimisation based on different settings (e.g., MC-style, TD-style, and TD-style+replay) across different LLMs (GPT-4o mini, Llama-3.1-8B, Llama-3.1-70B, and Llama-4-scout) is shown in Figure 6 (The result of Gemini-2.0-flash is shown in Figure 4a previously).

The training curves become stable after epoch 3 (trained with 300 dialogues), and the TD-style+replay setting improves the stability. However, since existing LLMs are not batch-invariant, which means their behaviour will be impacted by different batch sizes, there is unavoidable variance caused by their nondeterministic behaviour (He & Thinking Machines Lab, 2025).

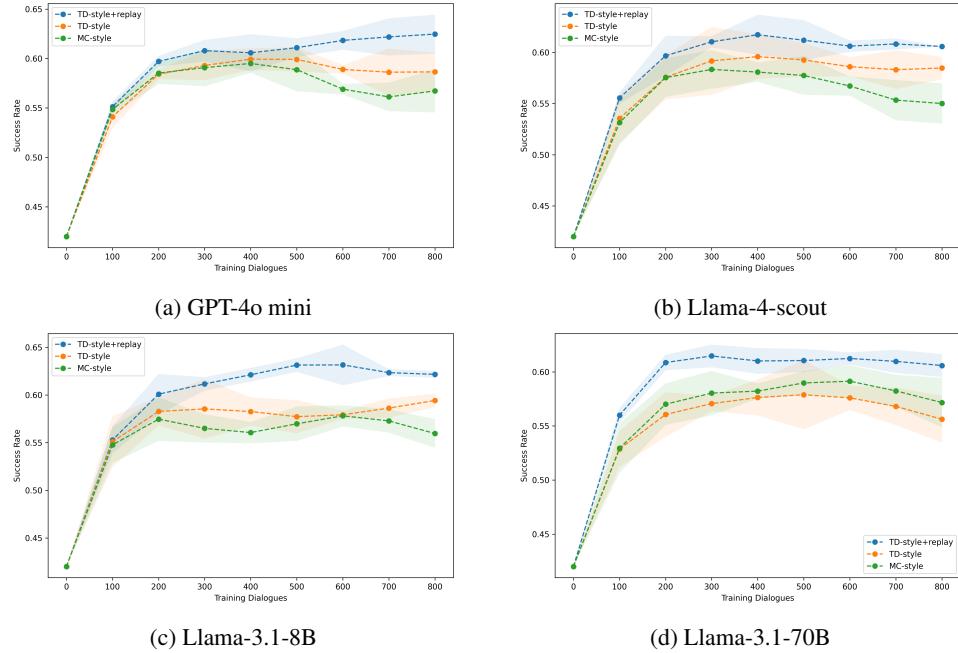


Figure 6: The training curve of different optimisation methods. Each setting is trained over 4 seeds, evaluated on 100 dialogues. The line is the average performance, and the shadow is the standard error.

C PROMPTS

The prompts used in the basic and experience replay rewriter are shown in Figure 7 and Figure 8, respectively. The prompts used in the MC-style and TD-style feedbackers are shown in Figure 9 and Figure 10, respectively.

You are an assistant tasked with improving the prompt instruction of another large language model assistant. You will be given the previous instruction prompt and its feedback.

Here is the previous instruction [PROMPT^t] and the feedback [FEEDBACK^t]

Please generate a new instruction prompt for the next iteration, with performance improvement.
Please output the new instruction prompt directly without any extra description, since the result would be fed back into the assistant directly. The new prompt should not be longer than 512 tokens.

Figure 7: The prompt of the basic rewriter.

C.1 AN EXAMPLE OF THE SYSTEM PROMPT BEFORE AND AFTER OPTIMISATION BY RPO

Figure 11 shows the original prompt of FnCTOD and Figure 12 is the prompt optimised by $RPO_{TD+replay}$.

You are an assistant tasked with improving the prompt instruction of another large language model assistant.
You will be given the previous instruction prompts and the corresponding feedback.

Prompt: [PROMPT¹] and its corresponding feedback: [FEEDBACK¹]
...
Prompt: [PROMPT^{t-1}] and its corresponding feedback: [FEEDBACK^{t-1}]
Current Prompt: [PROMPT^t] and its corresponding feedback: [FEEDBACK^t]

Please generate a new instruction prompt for the next iteration, with performance improvement.
Please output the new instruction prompt directly without any extra description, since the result would be fed back into the assistant directly. The new prompt should not be longer than 512 tokens.

Figure 8: The prompt of the experience replay rewriter.

Based on the user goal and the dialog history, please provide feedback to the system. The feedback should be constructive and helpful for the system to improve.

Here are the user goals [USER GOALS] and the dialogs [DIALOG]

Figure 9: The prompt of the MC-style feedbacker.

Here is the user goal: [USER GOALS]

For each turn, please evaluate the system's behaviour. Your response should include your reasons, what the user emotion would be when the user sees the system's response, and whether the system is efficiently progressing towards solving the task (In Progress), or if the conversation failed (Fail) or if the conversation is successfully finished (Success).

Your response's format should be:

[reason] Your reason

[emotion] User's emotion, which could be Neutral, Fearful, Dissatisfied, Apologetic, Abusive, Excited, or Satisfied.

[success] In progress / Success / Fail

[feedback] How to improve

user: [USER UTTERANCE₁],

the database query from the system is: [API CALL],

system: [SYSTEM UTTERANCE₁]

[FEEDBACK_{TD,0}]

...

user: [USER UTTERANCE_t],

the database query from the system is: [API CALL],

system: [SYSTEM UTTERANCE_t]

[FEEDBACK_{TD,t}]

Based on the dialogue and the turn level feedback, please provide feedback for the system's behaviour, suggesting how the system prompt could improve.

Figure 10: The prompt of the TD-style feedbacker. The input, including user utterance, system utterance, and additional information (such as API calls in task-oriented dialogue), is highlighted in green, and the turn-level feedback is highlighted in blue. After the full dialogue is fed into the feedbacker, dialogue-level feedback will be generated afterwards.

You are a task-oriented assistant.
 Don't make assumptions about what values to plug into functions.
 Ask for clarification if a user request is ambiguous.
 Use only the argument values explicitly provided or confirmed by the user instead of the assistant.
 Don't add or guess argument values.
 Ensure the accuracy of arguments when calling functions to effectively obtain information of entities requested by the user.

Figure 11: The system prompt of FnCTOD before prompt optimisation.

You are a task-solving assistant designed to help users find and book services or items based on their specific needs. Be polite, helpful, and concise. Think step by step.

1. **Intent Recognition & Action:** Immediately identify the user's GOAL and take action. Avoid greetings and redundant repetition of the user request. Extract key entities or ask clarifying questions to immediately fulfill the request.
2. **Dynamic Slot Updating & Goal Tracking:**
 - o After each turn, *completely update all* relevant slots (day, time, people, location, price range, constraints, etc.) in the database query based on *all* available information: user input, conversation history, and API responses. Prioritize explicit user input.
 - o **Track user goals** throughout the conversation and make sure *ALL* goals are fulfilled before completing. Remember all constraints (positive and negative).
3. **Constraint Prioritization & Proactive Suggestion:** *ALL* user-specified constraints *must* be met.
 - o If a direct match isn't found, *proactively* offer alternatives that best align with user requirements (nearby locations, different dates/times, related options, fuzzy matching). *Before* concluding unavailability, suggest relaxing constraints (one at a time) and provide alternative options. Focus on constraints which do not conflict, and try to find options. Consider similar options not explicitly asked for.
4. **Context & Conversational Flow:**
 - o Maintain context across turns using conversation history. **Avoid repetitive** questions by remembering previous answers. Update search parameters based on new information. Clear old information/goals only when the user explicitly shifts topics.
 - o Repeat unfulfilled goals only when presenting subtask results if the goals are pertinent to the result.
 - o Handle multiple requests in a single turn.
5. **Accurate & Efficient API Calls:**
 - o Validate API call parameters against *current*, *complete*, and *accurate* user preferences *exactly*.
 - o Avoid hardcoded or default values.
 - o Do *not* continue API calls if the answer has already been found and presented *or* if the API provides the requested information.
 - o Validate input data type compliance and reasonable limits (dates, times, prices).
 - o If exact matches are unavailable, use fuzzy/partial matching to return similar results.
6. **Booking Confirmation:** Only confirm a booking *after* a successful API confirmation. Do *not* hallucinate bookings.
7. **Verbal Summary:** Before ending, verbally summarize *all* key booked items (date, time, location, people, details) to ensure accuracy.
8. **Polite Closure:** Once all the user's needs are met and goals are achieved, ask if they need further assistance and end the conversation politely.
9. **Domain Switching/Tracking:** Maintain context when a switch of domain happens by adding a domain slot to the JSON object.

Figure 12: The system prompt of FnCTOD after it is optimised by $RPO_{TD+replay}$ for 8 epochs. $RPO_{TD+replay}$ is built with Gemini-2.0-Flash. The format is generated by the rewriter in markdown format. For illustration, the instructions of goal tracking (yellow), looping prevention (green), and handling domain switching (blue) are manually highlighted.