

# Bridging the Long-Term Gap: A Memory-Active Policy for Multi-Session Task-Oriented Dialogue

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## Abstract

Existing Task-Oriented Dialogue (TOD) systems primarily focus on single-session dialogues, limiting their effectiveness in long-term memory augmentation. To address this challenge, we introduce a **MS-TOD**<sup>1</sup> dataset, the first multi-session TOD dataset designed to retain long-term memory across sessions, enabling fewer turns and more efficient task completion. This defines a new benchmark task for evaluating long-term memory in multi-session TOD. Based on this new dataset, we propose a **Memory-Active Policy (MAP)** that improves multi-session dialogue efficiency through a two-stage approach. 1) *Memory-Guided Dialogue Planning* retrieves intent-aligned history, identifies key QA units via a memory judge, refines them by removing redundant questions, and generates responses based on the reconstructed memory. 2) *Proactive Response Strategy* detects and corrects errors or omissions, ensuring efficient and accurate task completion. We evaluate MAP on MS-TOD dataset, focusing on response quality and effectiveness of the proactive strategy. Experiments on MS-TOD demonstrate that MAP significantly improves task success and turn efficiency in multi-session scenarios, while maintaining competitive performance on conventional single-session tasks.

## 1 Introduction

Task-oriented dialogue (TOD) systems (Wang et al., 2021; He et al., 2022; Bang et al., 2023; Swamy et al., 2023a) have traditionally focused on single-session scenarios, overlooking the fact that real world interactions often span multiple sessions over extended periods. While LLMs have been introduced to improve TOD (Xu et al., 2024a,b; Chung et al., 2023; Heck et al., 2023a), most efforts remain confined to single-session settings and overlook long-term memory augmentation across multi-session interactions (Du et al., 2025). Moreover,

<sup>1</sup>Code and dataset will be released upon paper acceptance.

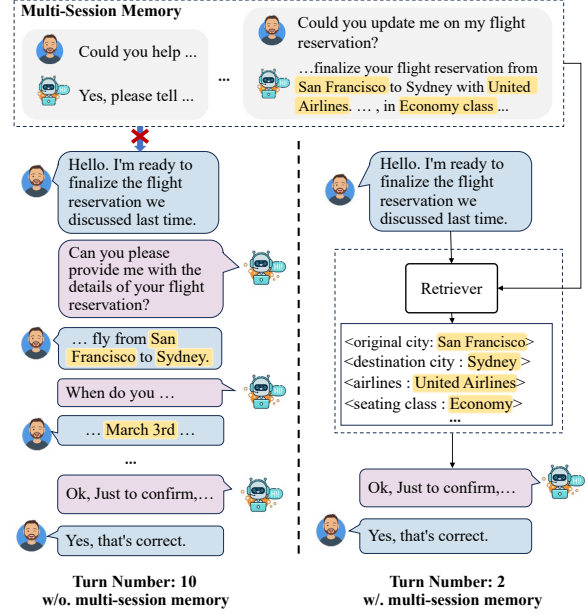


Figure 1: Task-oriented dialogue, without (left) vs. with (right) multi-session memory; the latter demands more turns of conversation.

existing TOD datasets (Stacey et al., 2024; Liu et al., 2024a; Budzianowski et al., 2018; Rastogi et al., 2020) are limited to single-session dialogues, leaving a gap in benchmarks for evaluating long-term memory retention across sessions.

As shown in Figure 1, single-session systems require users to restate details (e.g., flight times, seat preferences) in every session, leading to inefficiency and frustration. In contrast, multi-session memory enables seamless retrieval of prior context, supporting fewer turns and a more personalized experience. In contrast, multi-session memory allows systems to retrieve prior user-specific information—such as preferences or booking history—thereby reducing redundancy and supporting more efficient, goal-oriented interactions.

To bridge this gap, we introduce the **Multi-session Task-oriented Dialogue Dataset (MS-TOD)**, comprising 132 simulated speaker parti-

tions, each spanning over 20 sessions with diverse task goals derived from SGD (Rastogi et al., 2020). MS-TOD supports comprehensive evaluation of TOD systems to retrieve long-term context, maintain consistent task slots, and adapt responses across sessions. This also defines a novel task setting for evaluating long-term memory integration in multi-session TOD, where systems must leverage cross-session knowledge to support coherent and efficient task completion. While existing approaches in open-domain multi-session conversations focus on retrieving dialogue history or summaries (Lu et al., 2023; Zhong et al., 2024; Joko et al., 2024; Li et al., 2024a; Du et al., 2024), multi-session TOD system face additional demands: they must recall critical slot-value pairs, track evolving user intents, and proactively resolve missing or outdated information while minimizing redundant queries.

Therefore, we propose the **Memory-Active Policy (MAP)** to incorporate long-term memory in the multi-session TOD task. MAP consists of two core phases: (1) **Memory-Guided Dialogue Planning**, where an LLM generates an intent hypothesis retrieves relevant memory entries to support cross-session goal tracking. Furthermore, a memory judger identifies key QA units and refines them by removing redundant questions, distilling slot-level content for precise, context-aware response generation. (2) **Proactive Response Strategy**, which iteratively detects missing or mismatched slots by comparing predicted responses with task goals, actively engaging users to resolve incomplete slots, thereby reducing redundancy and ensuring smooth, goal-oriented interactions. Experimental results on MS-TOD demonstrate that MAP effectively improves dialogue coherence, response quality, task success rate, and dialogue efficiency in multi-session TOD. The main contributions include:

- We introduce **MS-TOD**, the first multi-session TOD dataset and benchmark task for evaluating long-term memory integration across sessions.
- We propose **MAP**, a two-stage framework that distills and leverages cross-session memory for efficient, minimal-turn task completion.
- We demonstrate that MAP consistently outperforms strong baselines across multiple metrics, confirming the effectiveness of its memory activation policy.

Settings	GPT-4 Score	Slot Acc.
<b>No Retrieval (Direct Prompting)</b>		
Current Session Context	2.60	0.13
Full Conversation Context	4.76	0.61
<b>Retrieval-Augmented Generation</b>		
BM25-Based Retrieval	5.90	0.53
Embedding-Based Retrieval	7.01	0.67
Hybrid Retrieval	7.04	0.68
<b>Oracle (Upper Bound)</b>		
Oracle	<b>8.51</b>	<b>0.82</b>

Table 1: Evaluation of confirmation-type response generation under different prompting and retrieval strategies.

## 2 Preliminary Experiments

To investigate the effectiveness of different strategies for handling dialogue history in multi-session task-oriented response generation, We conduct a preliminary study comparing direct prompting (Swamy et al., 2023b; Xu et al., 2024a) with retrieval-augmented generation (RAG) (Huang et al., 2024; Lu et al., 2023) in multi-session TOD.

Because standard TOD datasets lack multi-session dependencies, we construct a test set specifically for *confirmation-type* response generation (details in Section 3). Our pipeline includes (1) **Retrieval**. We explore three strategies for retrieving relevant historical dialogues: *sparse retrieval* (BM25 (Robertson and Zaragoza, 2009)), *dense retrieval* (text-embedding-small-3<sup>2</sup>), and a *hybrid* approach that combines both to leverage their complementary strengths. (2) **Response Generation**. GPT-4o-mini then generates confirmation-type responses by incorporating the retrieved dialogue history and task goal information.

As shown in Table 1, RAG consistently outperforms direct prompting. For instance, *dense retrieval* achieves 0.67 slot accuracy and a 7.01 GPT-4 score, surpassing full-context prompting (0.61 and 4.76, respectively). *Hybrid retrieval* further improves slot accuracy to 0.68 and the GPT-4 score to 7.04, demonstrating the value in combining sparse and dense strategies. Oracle retrieval (using ground-truth context) reaches 0.88 and 8.51, underscoring the need for more accurate retrieval strategies in multi-session TOD.

<sup>2</sup>OpenAI. text-embedding-3-small. 2025. OpenAI, <https://platform.openai.com/docs/guides/embeddings>.

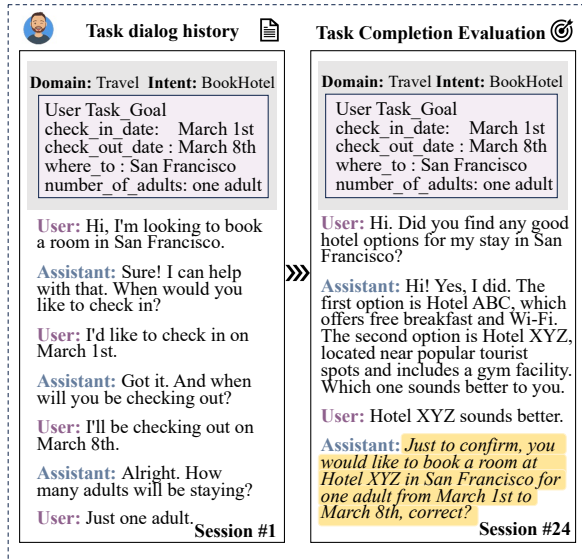


Figure 2: An Example of MS-TOD dataset.

### 3 Dataset

To systematically evaluate TOD systems requiring multi-session long-term memory integration, we develop the MS-TOD dataset, derived from the Schema-Guided Dialogue (SGD) dataset (Rastogi et al., 2020). Compared with existing TOD and open-domain datasets, MS-TOD uniquely supports multi-session memory retrieval, slot tracking, and intent continuity (see Appendix Table 9 for dataset comparison). MS-TOD comprises two subsets: a training subset for training the memory judge (Section 4.2) and an evaluation subset designed to assess multi-session memory activation and TOD response generation shown in Figure 2.

#### 3.1 Data Generation

**Multi-Session Dialogue Construction.** Because existing TOD corpora typically feature single-session interactions lacking structured multi-session dependencies, we create *three* dialogue sessions for each task in the SGD dataset. Compared with single-session dialogues, this design more closely simulates how users revisit and refine the same task at different times and in different contexts. We chose three sessions—rather than a higher number—to strike a balance between capturing realistic user behavior and avoiding repetitive dialogue data, particularly given that SGD tasks involve fewer than ten task slots. As a result, three sessions offer sufficient coverage of task variations without overpopulating the dataset. More details can be found in Appendix A.1.

**Confirmation-Type Response Annotation.** In

Attribute	Evaluation
Domains	16
Intentions	19
Task goals	956
Dialogues	2,861
Utterances	18,530
Avg. slots per task goal	4.24
Number of individuals	132
Avg. intentions per individual	5.45
Avg. sessions per individual	21.67
Avg. Utterances per individual	140.38

Table 2: MS-TOD dataset statistics for evaluation.

the final session of each task, we introduce confirmation-type annotations to mark utterances indicating the completion of long-term or recurring tasks. These annotations serve two primary functions: (1) **Guiding Memory Activation:** Highlighting key dialogue points to trigger long-term memory activation, summaries, or confirmations; and (2) **Supporting System Evaluation:** They enable evaluation of the system’s ability to recognize and record cross-session information or long-term goals during dialogue strategy assessment.

#### 3.2 Memory Bank Construction

Since multi-session interactions occur at the individual level, we group sessions into *Individual Memory Banks* (Figure 2), each storing an individual’s historical dialogues to maintain continuity and enable adaptive responses. Each bank contains over 20 sessions spanning more than six distinct user intentions (Table 2), with one evaluation session per intent to assess confirmation-type generation. Task goals are included to support memory activation and task handling. We employ a GPT-4-based generator to extract intent descriptions and construct task-specific QA pairs (Appendix A.2), enabling efficient and intention-aware memory retrieval across domains. Additional dataset details appear in Appendix B.1 and B.2.

MS-TOD is derived from the Schema-Guided Dialogue (SGD) dataset, selected for its broad domain coverage, schema-driven design, and support for multi-domain interactions. Our memory bank structure (20 sessions, 6+ intents) reflects typical slot-intent patterns in SGD and aligns with prior multi-session benchmarks (Appendix B.5).

**Human Validation.** To ensure the quality and coherence of the constructed dataset, we conducted a multi-stage manual validation process to verify intent accuracy, slot-value correctness, dialogue

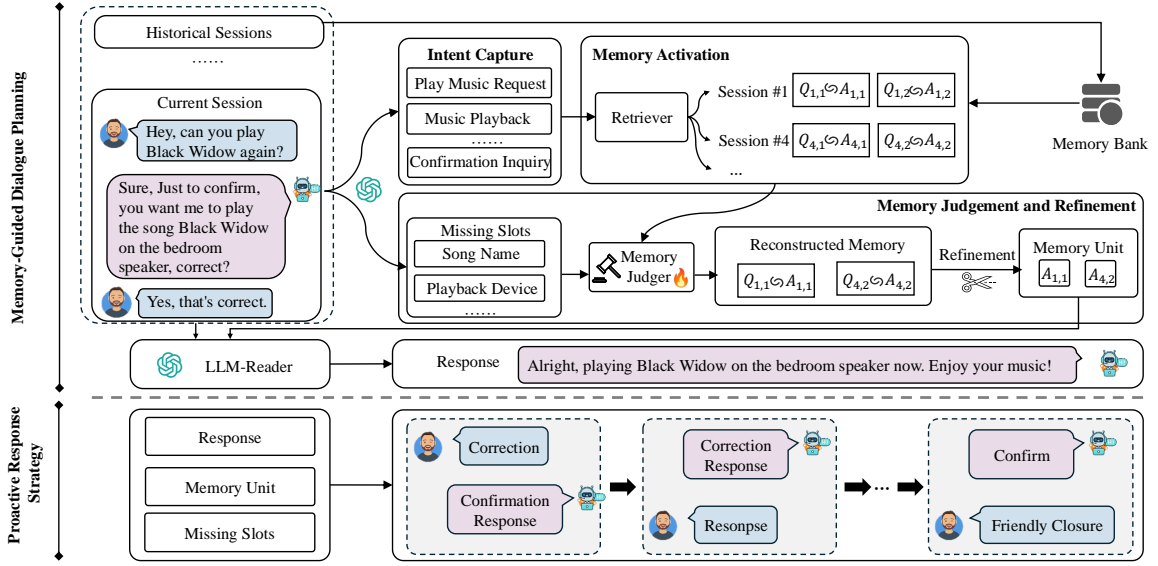


Figure 3: Overview of our MAP framework, which comprises Memory-Guided Dialogue Planning and Proactive Response Strategy.

coherence, and confirmation-response alignment. Full validation procedures are described in Appendix B.3.

## 4 Memory-Active Policy

To address the need for long-term memory and multi-session context in TOD, the Memory-Active Policy (MAP) combines memory-driven dialogue planning with a proactive policy strategy as shown in Figure 3.

### 4.1 Task Definition

The objective of this task is to generate a natural language response  $r$  based on the provided dialogue context  $c$  and individual memory bank  $M$ . The dialogue context  $c$  represents the ongoing interaction, comprising chronologically ordered user utterances  $u_j$  and system responses  $r_j$ . The individual memory bank  $M$  consists of memory representations from multiple dialogue sessions, where each session provides an intent description  $k_i$  and a corresponding set of QA pairs  $v_i$ . Formally, we define:  $M = \{(k_i, v_i)\}_{i=1}^N$ ,  $v_i = \{(q_{ij}, a_{ij})\}_{j=1}^n$ . Here,  $k_i$  represents the session’s high-level intent, while  $v_i$  stores detailed task-related information. This structured design facilitates efficient retrieval and utilization of long-term user-specific memory.

The response  $r$  is generated by a large language model  $LLM$  that integrates  $c$  and  $M$ , ensuring semantic coherence, memory relevance, and task slot accuracy. Formally, the optimal response is obtained by maximizing the conditional probability

distribution:

$$r^* = \arg \max_{r \in \mathcal{R}} P(r | c, M), \quad (1)$$

where  $\mathcal{R}$  denotes the set of all possible responses. This approach emphasizes understanding the dialogue context and leveraging individual memory to produce coherent and relevant responses.

### 4.2 Memory-Guided Dialogue Planning

Memory-Guided Dialogue Planning consists of two key steps: (1) Intent Capture and Memory Activation, where the system identifies and retrieves relevant memories aligned with the user’s intentions; (2) Memory Judgement and Refinement, which detects missing task slots, and re-ranks relevant memories to ensure optimal information recall for response generation.

**Intent Capture and Memory Activation.** Given the dialogue context  $c_i$ , we use LLM (GPT4o-mini) to generate a high-level intent description  $k_i$ , which summarizes the user’s objective in the current session. The intent description  $k_i$  is then used to retrieve relevant memory units from the long-term memory  $M$ , represented as  $M = \{(k_j, v_j)\}_{j=1}^m$ , where  $k_j$  is an intent-related key and  $v_j$  is the corresponding structured information, such as paired questions and answers. Using an embedding model,  $k_i$  is mapped to a dense representation and compared with  $k_j$  to activate the most relevant memory units  $v_i$ . These activated memory units  $v_i$ , containing structured information such as task-related



questions and answers, are then used to guide subsequent dialogue processing.

**Memory Judgement and Refinement.** To guide accurate memory selection, we first identify missing task information using a Chain-of-Thought (CoT) prompting strategy (Wei et al., 2022), which generates a hypothesized missing slot query  $q_{\text{miss}}$  based on the current dialogue context  $c_i$ . This missing query serves as a proxy for what information is needed from memory to complete the task. We then assess the relevance of each QA pair in the retrieved memory using a memory judger instantiated by LLaMA 3.1-8B (Meta AI, 2024). Given  $c_i$ ,  $q_{\text{miss}}$  and  $(q_{j,u}, a_{j,u})$ , the judger estimates:

$$s_{j,u} = P(y = 1 | (c_i, q_{\text{miss}}, (q_{j,u}, a_{j,u}))) \quad (2)$$

where  $y = 1$  indicates that the QA pair contributes to the task goal, while  $y = 0$  indicates irrelevance. The model is trained with cross-entropy loss:

$$\mathcal{L} = - \sum y \log s_{j,u} + (1 - y) \log(1 - s_{j,u}) \quad (3)$$

To balance retrieval relevance and judger evaluation, we re-rank all QA pairs using a weighted combination of initial retrieval score  $s_{f,ju}$  and judger score  $s_{ju}$ :

$$s_{f,ju} = \alpha \cdot s_{\text{prev},ju} + (1 - \alpha) \cdot s_{ju}, \quad (4)$$

The top 5 QA pairs  $v_{\text{selected}}$  with the highest  $s_{\text{final},ju}$  scores are selected for refinement.

**Memory Refinement.** In the refinement stage, we clean and restructure the selected QA pairs to remove noise and improve response grounding. Specifically, we discard auxiliary questions  $q_{j,u}$  and retain only the core answers  $A_{\text{core}} = \{a_{j,u}\}$ . These core answers are concatenated into the dialogue context to form a memory-enhanced prompt for the generation module. This step ensures that only high-relevance, low-noise content is passed forward for response planning.

### 4.3 Proactive Response Strategy

The response generation phase synthesizes the dialogue context  $c$  and pruned memory  $A_{\text{core}}$  (from memory reconstruction) into a confirmation response  $r$ . Using  $\text{LLM}_{\text{Reader}}$ , the system evaluates if integrated memory supports task completion:

$$r = \text{LLM}_{\text{Reader}}(c, A_{\text{core}}) \quad (5)$$

where  $r$  serves dual purposes: (1) providing task guidance and (2) explicitly verifying memory relevance to user goals (see Appendix A.3 for details).

To provide more comprehensive responses to user queries, we propose a proactive dialogue policy. Based on the generated response  $r$ , we identify missing or incorrect slots within the dialogue. This results in a set of slots, denoted as  $L = \{l_1, l_2, \dots, l_n\}$ , where each  $l_i$  represents a missing or erroneous slot. We design an agent to simulate the user, explicitly informing it of the slot set  $L$ . The user agent then interacts with our dialogue model in an interactive conversation to address the identified slots.

At each dialogue turn, a supervisor (played by an LLM) evaluates whether the conversation accurately fulfills the slot information requirements. If a slot  $s_i$  is successfully resolved during the interaction, it is removed from  $L$ . Mathematically, the update to the slot set is expressed as:

$$S \leftarrow L \setminus \{l_i\} \quad (6)$$

The interaction continues for multiple turns until the slot set becomes empty,  $L = \emptyset$ , ensuring all missing or erroneous slots are resolved.

## 5 Experiments

### 5.1 Experimental Setups

**Evaluation Metrics.** We use four core metrics to evaluate model performance: **GPT-4 score**, **Joint Goal Accuracy (JGA)**, **Dialogue Turn Efficiency (DTE)**, and **Success Rate (S.R.)**. GPT-4 Score (1–10)<sup>3</sup> reflects response quality based on fluency, coherence, and informativeness. JGA measures slot prediction accuracy, DTE captures the number of turns required to complete a task, and S.R. indicates whether the user goal is achieved. To support analysis, we report auxiliary metrics including **Recall@k** for memory retrieval accuracy, **Slot Accuracy** for value correctness, and **BLEU** and **ROUGE** for generation overlap. **Human evaluation** further assesses Accuracy, Informativeness, and Coherence, with **A.I.C.** denoting their average. Annotation details are provided in Appendix C.3.

**Baselines.** We comprehensively evaluate MAP against three baseline categories:

- **General-purpose LLMs.** We evaluate prompting-based dialogue performance with

<sup>3</sup>GPT4-as-the-judge prompts can be found in Appendix A.4

Model	Setting	GPT4	JGA	DTE	S.R.
LLaMA3-8B	w/o MAP	4.89	<b>0.64</b>	5.37	0.82
	w/ MAP	<b>6.39</b>	0.63	<b>3.46</b>	<b>0.92</b>
Qwen-7B	w/o MAP	6.26	0.66	4.93	0.83
	w/ MAP	<b>6.81</b>	<b>0.66</b>	<b>4.31</b>	<b>0.87</b>
Mistral-7B	w/o MAP	6.20	0.73	2.52	1.00
	w/ MAP	<b>6.48</b>	<b>0.80</b>	<b>1.21</b>	<b>1.00</b>
GPT4o-mini	w/o MAP	6.93	0.67	6.03	0.88
	w/ MAP	<b>7.14</b>	<b>0.70</b>	<b>3.19</b>	<b>0.99</b>

Table 3: Performance comparison of general-purpose LLM models with and without long-term memory integration. The w/o MAP setting uses full-context prompting, feeding the entire dialogue history as input, while w/ MAP leverages memory active policy to retrieve and utilize relevant long-term memory.

instruct models including LLaMA3-8B (Touvron et al., 2024), Qwen2.5-7B (Team, 2024c), Mistral-7B (Team, 2024a), and GPT-4o-mini (Team, 2024b).

- **Traditional Task-Oriented Dialogue Systems.** To assess MAP in structured DST scenarios, we compare with task-specific fine-tuned BERT-DST (Chao and Lane, 2019), AutoTOD (Xu et al., 2024a), and LDST (Feng et al., 2024). Among these, AutoTOD incorporates an external memory module to track user goals across turns.
- **Long-term Summarization Baseline.** We additionally implement a summarization-based baseline inspired by ChatCite (Li et al., 2024c), which produces concise history summaries for each session. The same inference model (GPT-4o-mini) is used across all settings to ensure fairness.

To ensure a fair assessment of generalization, all models are evaluated on a held-out multi-session test set that is excluded from all training processes.

## 5.2 Main Results

**Comparison with General-purpose LLMs.** We conduct the experiments comparing full context prompting and our MAP framework in the metric of GPT4, JGA, DTE, and S.R. As shown in Table 3, MAP demonstrates consistent performance gains over baseline prompting methods. For instance, applying MAP to Mistral-7B increases JGA from 0.73 to 0.80 and S.R. from 0.83 to 0.87. Notably, LLaMA3-8B, Qwen-7B, and GPT-4o-mini also show significant improvements in both JGA and S.R. when integrated with MAP. In terms of

Model	GPT4	JGA	DTE	S.R.
Bert-DST*	-	0.067	-	-
LDST*	-	0.234	-	-
AutoTOD <sup>†</sup>	6.49	0.440	7.80	0.81
ChatCite	6.59	0.660	4.71	0.84
MAP	<b>7.14</b>	<b>0.698</b>	<b>3.19</b>	<b>0.99</b>

Table 4: Performance comparison of traditional TOD models, summary-based methods, and MAP. Models marked with \* focus on DST only. <sup>†</sup> indicates simplified AutoTOD pipeline. The ChatCite represents a long-term memory baseline using dialogue summarization.

Model	Confirmation		Multi-Turn	
	w/o MAP	w/ MAP	w/o MAP	w/ MAP
LLaMA3-8B	1.64	<b>1.99</b>	1.60	<b>2.03</b>
Qwen-7B	1.46	<b>1.88</b>	1.48	<b>1.77</b>
Mistral-7B	1.79	<b>1.99</b>	2.04	<b>2.18</b>
GPT4o-mini	1.86	<b>2.27</b>	1.72	<b>1.85</b>

Table 5: Human evaluation results based on the average A.I.C., which is the mean of Accuracy, Informativeness, and Coherence. w/ denotes with, w/o denotes without.

response quality, **GPT-4 score** rises notably for all models; for example, LLaMA3-8B achieves the largest gain, from 4.89 to 6.39. Regarding **DTE**, MAP considerably shortens the required turns, with reductions of 35.6% for LLaMA3-8B, 12.6% for Qwen-7B, 52.0% for Mistral-7B, and 47.1% for GPT-4o-mini. These results demonstrate that integrating long-term memory enhances both response quality and conversation efficiency.

**Comparison with Traditional TOD and Long-term Summarization Models.** As no prior model explicitly targets multi-session TOD, we compare MAP with traditional DST baselines (BERT-DST, LDST) and full-pipeline systems (AutoTOD). As shown in Table 4, MAP substantially outperforms these models, achieving a JGA of 0.698 (vs. 0.440 for AutoTOD) and reducing DTE from 7.8 to 3.19. We also evaluate against a summarization-based approach (ChitChat), where MAP again achieves superior results: higher GPT-4 score (7.14 vs. 6.98), better JGA (0.70 vs. 0.66), shorter DTE (3.19 vs. 4.71), and improved success rate (0.99 vs. 0.84). These results highlight the effectiveness of MAP’s memory integration and proactive strategy in enhancing both accuracy and interaction efficiency.

**Human Evaluation.** We conduct human evaluation to further assess the effectiveness of the MAP structure across two key dialogue settings: (1) confirmation-type responses after memory-guided dialogue planning, and (2) multi-turn dialogues un-

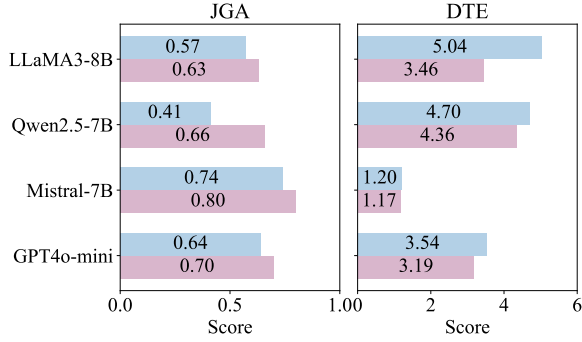


Figure 4: Comparison of Hybrid RAG (blue) vs. MAP (purple) across four LLMs on two metrics: JGA and DTE.

der the proactive response strategy. Evaluators are instructed to rate responses based on Accuracy (binary), Informativeness (Likert 0–3), and Coherence (0–3). A weighted average score (A.I.C.) is used to summarize overall performance. As shown in Table 5, MAP consistently improves perceive response quality across all metrics. All evaluations are conducted in a blind review setup. Further annotation guidelines, examples, and scoring distributions are provided in Appendix C.3.

### 5.3 Extended Evaluation

To examine the applicability of our QA memory framework beyond multi-session TOD, we evaluate MAP on two widely-used DST benchmarks, SGD and MultiWOZ2.2. Although both benchmarks target dialogue state tracking (DST), they differ in annotation formats and domain complexity, leading to different baseline sets (Table 7). On SGD, MAP achieves a state-of-the-art JGA of 0.846, surpassing strong baselines such as LDST (Feng et al., 2023), GOLOMB (Gulyaev et al., 2020), SGP-DST (Ruan et al., 2020), and TS-DST (Du et al., 2022), and performs comparably to LDST on AGA. On MultiWOZ2.2, MAP\* attains a JGA of 0.879, significantly outperforming prior models including TRADE (Wu et al., 2019a), TripPy (Heck et al., 2020), and SDP-DST (Lee et al., 2021). We attribute the superior performance to QA memory’s ability to capture slot dependencies more effectively in smaller domain settings, confirming its adaptability and robustness across datasets.

### 5.4 Ablation Study

We conduct ablations to evaluate contributions of key MAP components, including the judger-refinement module and proactive response strategy.

**Judgement-Refinement.** We conduct abla-

tion experiments to analyze the contribution of the judger and refinement components in MAP. Compared with a strong retrieval-based baseline, we evaluate MAP with and without the judger-refinement module, using the same Hybrid RAG-based memory activation. As shown in Figure 4, MAP with judger-refinement consistently outperforms the baseline across model backbones. On Qwen2.5-7B, JGA rises from 0.41 to 0.74, and on GPT-4o-mini, DTE drops from 4.30 to 3.19, highlighting the benefit of goal-aware filtering and structured memory usage.

*To isolate the effect of the Memory Judger,* we remove it from the pipeline while keeping the refinement step. The judger uses Chain-of-Thought (CoT) prompting to infer missing task slots and assess the alignment of QA pairs with current dialogue goals. This reasoning-guided filtering improves memory relevance, yielding a Recall@5 gain of 7.7% on average across models (Appendix Figure 6); for instance, text-embedding-3-small improves from 0.792 to 0.832.

*To assess the effect of the Refinement module,* we remove it while retaining the judger. Refinement restructures selected QA pairs by discarding auxiliary questions and preserving only core answers aligned with intent. As shown in Table 6, removing Refinement causes performance to drop: JGA decreases from 0.70 to 0.64, GPT-4 Score from 7.14 to 6.94, and Success Rate from 0.99 to 0.88, while DTE increases from 3.19 to 4.33. These results demonstrate that both components are essential for precise memory integration and efficient multi-session dialogue.

**Proactive Response Strategy.** MAP identifies incomplete or inconsistent slot values by comparing predicted responses with task goals, and proactively engages the user to resolve them. The effectiveness of this strategy is reflected in the observed improvement from 0.68 slot accuracy prior to correction to a task success rate of 0.99 after correction. These results demonstrate its critical role in early error resolution and goal fulfillment. Detailed statistics are provided in Appendix C.2.

### 5.5 Case Study

In our case study, we compared four methods for generating confirmation responses: (1) Direct Prompting with full conversation history, (2) Hybrid RAG retrieving relevant dialogue history, (3) Hybrid RAG retrieving a summary of the conversa-

Model Variant	GPT-4 Score	JGA	DTE	S.R.
MAP	<b>7.14</b>	<b>0.70</b>	<b>3.19</b>	<b>0.99</b>
- w/o refinement	6.94	0.64	4.33	0.88

Table 6: Impact of memory refinement in the memory activation module. Refinement improves JGA, GPT-4 score, and overall task success.

Dataset	Methods	JGA	AGA
SGD	SGD Baseline	0.254	0.906
	GOLOMB	0.465	0.750
	SGP-DST	0.722	0.913
	TS-DST	0.786	0.956
	LDST	0.845	<b>0.994</b>
	MAP*	<b>0.846</b>	0.965
MultiWOZ 2.2	SGD Baseline	0.420	-
	TRADE	0.454	-
	DS-DST	0.517	-
	TripPy	0.530	-
	TOATOD	0.638	-
	SDP-DST	0.576	0.985
	LDST	0.607	<b>0.988</b>
	MAP*	<b>0.879</b>	0.976

Table 7: Results of different methods on SGD and MultiWOZ 2.2. MAP\* is a single-session variant of MAP, where the Memory Judger is disabled while retaining the QA memory.

tion, and (4) MAP with intention-based QA memory. As shown in Figure 5, Direct Prompting introduces noise, while Hybrid RAG variants often omit key task slots due to retrieval inaccuracies. In contrast, MAP consistently produces accurate, concise responses with fewer errors. These findings indicate that MAP with intention-based QA memory better preserves key task information and reduces errors in confirmation generation than other baselines. More details are provided in Appendix D.

## 6 Related Works

### 6.1 Task-Oriented Dialogue Dataset

TOD datasets are typically constructed via either Machine-to-Machine (M2M) (Shah et al., 2018; Rastogi et al., 2020) or Wizard-of-Oz (WOz) setups (Wen et al., 2017; Budzianowski et al., 2018). M2M datasets (e.g., SGD, STAR) provide schema-driven task flows, while WOz-based datasets (e.g., MultiWOZ, FRAMES) offer more natural but annotation-heavy dialogues. Recent efforts aim to improve realism and domain diversity (Zhang et al., 2022; Hu et al., 2023; Dai et al., 2022; Xu et al., 2024b; Li et al., 2024b), yet existing benchmarks primarily assume single-session tasks. There re-

Session 23 Evaluation - <i>Intention: The user intends to listen to songs.</i>	
Dialogue Context	User: Can you play 'Drive' again? Assistant:
Confirmation Response (Direct Prompting with the Full Conversation History)	Sure! Just to confirm, you'd like me to play the song "Drive" on the <b>bedroom speaker</b> again. Should I start it now? <i>Also, would you like me to check out some tickets for ... (Extra Noise)</i>
Confirmation Response (Hybrid RAG with Retrieved History)	Sure! Let me play "Drive" for you once more. By the way, have you decided on the number of tickets you'd like to buy for Bill Callahan's concert? It's coming up on March 10th in Los Angeles! ( <i>Wrong Answer</i> )
Confirmation Response (Hybrid RAG with Summary)	Sure! I've started playing "Drive" again. Is there anything else you'd like? ( <i>Key Slot Omission</i> )
Confirmation Response (MAP)	Sure! Just to confirm, you'd like me to play the song "Drive" on the <b>bedroom speaker</b> again. Should I start it now? ( <i>Right Answer</i> )

Figure 5: Case study.

mains a notable gap in datasets designed for multi-session TOD, where tracking long-range goals and user intents is essential.

### 6.2 Task-Oriented Dialogue Systems

Traditional TOD systems adopt modular pipelines for NLU, DST, and response generation (Wu et al., 2019b; Peng et al., 2018), later unified into end-to-end models trained on annotated dialogues (Wen et al., 2017; Wang et al., 2020). With the rise of LLMs, recent work explores their use in zero-shot and fine-tuned TOD (Madotto et al., 2021; Bang et al., 2023), often achieving strong results on intent recognition and slot filling. In parallel, long-term memory (LTM) methods such as ChitChat (Li et al., 2024c), MemoryBank (Zhong et al., 2024), and LoCoMo (Maharana et al., 2024) support extended context retention through summarization or heuristic filtering, but lack structured memory aligned with task goals. Most assume single-session dialogues and overlook challenges in maintaining multi-session goal continuity. This work addresses these gaps by introducing a memory-active policy for long-range, goal-aware tracking.

## 7 Conclusion

This study introduces a multi-session TOD task and the MS-TOD dataset, which features diverse task goals and structured memory banks across sessions. To address the challenges of long-term context integration, we propose MAP, a memory-augmented framework that combines dialogue planning with a proactive response strategy for efficient task completion. Experimental results show that MAP significantly reduces dialogue turns, improves response quality, and boosts task success rate, outperforming both direct prompting and existing long-term retrieval methods.



## Limitation

While our model demonstrates effectiveness on the current dataset, several limitations remain. First, our experiments are limited to locally deployable LLM models, and we have not explored the potential benefits of scaling to larger models, which may yield further improvements. Second, our approach does not incorporate external knowledge bases or internet search functionality, which could enhance contextual understanding and factual accuracy. Lastly, the model’s generalizability to broader domains and more complex real-world scenarios remains untested, necessitating further evaluation across diverse datasets and tasks. Future work will address these limitations by expanding model scalability, integrating external knowledge sources, and conducting more comprehensive evaluations.

## Ethics Statement

Our research enhances multi-session task-oriented dialogue through memory-augmented processing while complying with ethical standards. All datasets are public and contain no personally identifiable information; no user-sensitive data are collected, and no human subjects are involved. Model evaluations are conducted by three trained research assistants, each paid \$20/hour, above the local average. We acknowledge risks including misinformation, algorithmic bias, and issues specific to long-term memory, such as retaining outdated user preferences or privacy concerns from cross-session data accumulation. These are addressed through evaluation safeguards, memory control mechanisms, and design principles promoting transparency, fairness, and accountability.

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817	Chain of thought prompting elicits reasoning in large		
818	language models. <i>arXiv preprint arXiv:2201.11903</i> .	<b>A Prompts</b>	873
819	Tsung-Hsien Wen, David Vandyke, Nikola Mrkšić, Mil-	<b>A.1 Prompt of dialogue generation</b>	874
820	ica Gasic, Lina M Rojas Barahona, Pei-Hao Su, Ste-	We designed a multi-session dialogue prompt (as	875
821	fan Ultes, and Steve Young. 2017. A network-based	shown in Figure 7) that generates multi-session di-	876
822	end-to-end trainable task-oriented dialogue system.	alogue data based on input dialogue intent, task	877
823	In <i>Proceedings of the 15th Conference of the Euro-</i>	goal, and target session count. Additionally, during	878
824	<i>pean Chapter of the Association for Computational</i>	the generation process, we annotate whether each	879
825	<i>Linguistics: Volume 1, Long Papers</i> , pages 438–449.	utterance is a confirmation response. These annota-	880
826	Chien-Sheng Wu, Andrea Madotto, Ehsan Hosseini-	tions, after manual verification, will be used in the	881
827	Asl, Caiming Xiong, Richard Socher, and Pascale	main experiment for confirmation-type response	882
828	Fung. 2019a. <a href="#">Transferable multi-domain state gener-</a>	generation.	883
829	<a href="#">ator for task-oriented dialogue systems</a> . <i>Preprint</i> ,		
830	<i>arXiv:1905.08743</i> .	<b>A.2 Prompt of Task Slot Query Generation</b>	884
831	Chien-Sheng Wu, Andrea Madotto, Ehsan Hosseini-Asl,	During the evaluation process, we design a prompt	885
832	Caiming Xiong, Richard Socher, and Pascale Fung.	(as shown in Figure 8) that generates a query corre-	886
833	2019b. Transferable multi-domain state generator	sponding to the missing task attributes based on the	887
834	for task-oriented dialogue systems. In <i>Proceedings</i>	current dialogue context and task objectives. The	888
835	<i>of the 57th Annual Meeting of the Association for</i>	input to this prompt is the dialogue context history	889
836	<i>Computational Linguistics</i> , pages 808–819.	and the generated task objectives. This query is	890
837	Di Wu, Hongwei Wang, Wenhao Yu, Yuwei Zhang,		
838	Kai-Wei Chang, and Dong Yu. 2025. <a href="#">Longmemeval:</a>		



Attribute	Train
Domains	16
Intentions	22
Task goals	4,534
Dialogues	13,441
Utterances	89,152
Avg. slots per task goal	4.49
Number of individuals	565
Avg. intentions per individual	6.24
Avg. sessions per individual	23.79
Avg. Utterances per individual	157.80

Table 8: MS-TOD Subset Statistics for Memory Judger Training.

then used as input to the memory judger to assist in selecting QA memory units that align with the task objectives.

### A.3 Prompts of Confirmation Response Generation

In the evaluation process, we employed a confirmation-type response generation approach to assess the integration performance of multi-session memory in task-oriented dialogues. We designed the prompt as shown in Figure 9, which leverages the dialogue context, task objectives, and activated memory units to generate responses.

### A.4 Prompts of GPT4 Evaluation

During the evaluation process, we employed a GPT-4 prompt (as shown in Figure 11) to assess the quality of confirmation-type responses. This prompt evaluates the response holistically from four perspectives: requirement alignment, content accuracy, language quality, and comparison to the reference answer. The input to this prompt includes the dialogue history, task objectives, the reference response, and the model-generated response. This design ensures that the evaluation of the response is not solely based on the dataset’s reference reply but also takes into account multiple factors such as whether the task objectives are met and the overall quality of the response. Such an evaluation approach is more comprehensive.

### A.5 Prompts of Dialogue State Tracking

we used a prompt modified from (Heck et al., 2023b) (as shown in Figure 10) that generates the dialogue state for each user turn in the dialogue.

Let

$$A_1 = P \oplus \text{system} : M_1 \oplus \text{user} : U_1$$

$$A_t = A_{t-1} \oplus \text{system} : M_t \oplus \text{user} : U_t, \quad \forall t \in [2, T]$$

where  $P$  is the task description which provides the model with instructions for how to process a dialogue between a system  $M$  and a user  $U$ . In contrast to (Heck et al., 2023b),  $P$  does not include the detailed description for slots to challenge ChatGPT’s ability to understand the meaning of the slots. Apart from that, ChatGPT often generated answers with excessively detailed explanations, deviating from the expected response format. To address this issue, a prompt that includes "No explanation!" as an instruction to ChatGPT not to provide detailed explanations was introduced (Feng et al., 2023) and we added this to our prompt.

## B Dataset

### B.1 Dataset for Memory Judger

To ensure that the memory judger generalizes across different domains and scenarios, we generated the training dataset (as shown in Table 8) using the same method described in the main text. The dataset spans 16 domains, 4,534 task goals, and 13,411 dialogues, involving a total of 565 individuals, each with an average of 6.24 intentions. Beyond training the memory judger, this dataset can also serve as an alternative evaluation set for broader benchmarking.

### B.2 Dataset Structure

MS-TOD encompasses multiple individual task-oriented dialogue datasets, each consisting of several sessions. We present an example of one session (as shown in Figure 12) from an individual. This session includes a *session\_id*, where a larger value indicates a more recent timestamp. The domain represents the specific field or area of the dialogue. The *reference\_dialogue\_id* corresponds to the *dialogue\_id* in the original SGD dataset that shares the same task objective. The *exist\_confirmation* indicates whether the session contains a confirmation-type response and whether it is an evaluation target. The intent represents the specific purpose or goal of the dialogue. The content stores the actual dialogue text. The *task\_goal* includes task slots and their corresponding attribute values. Each individual contains dozens of session data structured as described above.



Dataset	Task Type	Multi-Session?	Grounded Memory?	User Intention?	Retrieval Support?	Memory Format
MULTIWOZ (Hu et al., 2023)	TOD	✗	✗	✓	✗	–
SGD (Rastogi et al., 2020)	TOD	✗	✓	✓	✗	schema
TOAD (Liu et al., 2024b)	TOD	✗	✗	✓	✗	–
LUCID (Stacey et al., 2024)	TOD	✗	✓	✓	✗	latent goal
MSC (Xu et al., 2022)	OD	✓	✓	✓	✓	dialogue history
CC (Jang et al., 2023)	OD	✓	✓	✗	✓	persona/dialogue history
MEMORYBANK (Zhong et al., 2024)	OD	✓	✓	✗	✓	dialogue history
LoCoMo (Maharana et al., 2024)	OD	✓	✓	✗	✓	dialogue history
LONGMEMEVAL (Wu et al., 2025)	OD	✓	✓	✗	✓	dialogue history
MS-TOD (ours)	TOD	✓	✓	✓	✓	qa memory/dialogue history

Table 9: Comparison of MS-TOD with representative Task Oriented Dialogue (TOD) and Open Domain (OD) datasets along memory-related attributes.

### B.3 Human Validation Protocol

To ensure the realism, coherence, and usability of MS-TOD, we apply a structured human validation process during dataset construction. This process involves three research assistants with prior experience in natural language processing and dialogue systems. The validation pipeline includes the following stages:

1. **Intent and Slot Accuracy Check.** For each dialogue turn derived from the SGD intent annotations, annotators verify whether the intent is preserved and whether all required slot values are present and semantically correct.
2. **Redundancy Removal.** Annotators manually review and remove multi-session dialogues that contain excessive repetition across sessions, which could undermine diversity and realism.
3. **Confirmation Accuracy Validation.** For final-session confirmation-type utterances, annotators examine whether the confirmed slot values align with the task goal. Mismatched, ambiguous, or hallucinated confirmations are flagged and discarded.
4. **Dialogue Coherence Filtering.** Dialogues that fail to complete any defined task goal are considered incoherent. Sessions missing necessary confirmation-type turns are also excluded to ensure logical task flow.
5. **Intent Redundancy Filtering.** Episodes exhibiting unnatural repetition of similar intents across turns or sessions are excluded, as such patterns deviate from realistic multi-session user behavior.

This multi-stage quality control procedure yields a filtered evaluation subset used for system benchmarking. The validation process ensures that the dataset aligns with realistic task-oriented dialogue patterns and supports the evaluation of multi-session memory-aware dialogue systems.

### B.4 Intent-driven QA Memory

For each historical session, we generated an intent description and the corresponding QA memory (as shown in Figure 13) for the objectives of that intent description. The QA memory consists of multiple QA pairs, where each query is a question about a task attribute under that intent, and the answer is the slot value corresponding to that task attribute.

### B.5 Dataset Design Rationale

**Choice of Seed Dataset.** We select the Schema-Guided Dialogue (SGD) dataset as the foundation for constructing MS-TOD. Compared to other popular benchmarks like MultiWOZ, SGD provides broader domain coverage, a larger and more diverse set of user intents, and a schema-driven annotation format that supports extensibility and dynamic intent representation. These characteristics make SGD more suitable for modeling realistic, multi-domain, and multi-session interactions. A detailed comparison is shown in Table 10.

**Design of Memory Bank Structure.** Each MS-TOD memory bank contains 20 sessions involving more than six distinct user intents. This structure is informed by two factors. First, prior multi-session datasets such as LoCoMo (?) typically use memory segments with 20+ sessions, providing a reference for session scale under long-term memory settings. Second, based on analysis of the SGD schema, each user intent generally corresponds to fewer than 10 slot types. Organizing 3 sessions per intent enables

natural progression while minimizing redundancy. As a result, grouping 6–8 distinct intents yields a total of around 20 sessions per memory bank, balancing diversity, realism, and memory demand.

## C Supplementary Experimental Results

### C.1 Memory Activation Comparision

Table 12 compares the performance of different activation modules on memory retrieval. **text-embed3-small** achieves the highest recall across all thresholds, with 0.702 at Recall@3, 0.792 at Recall@5, and 0.905 at Recall@10, demonstrating superior retrieval capability. Among other models, **nv-embed-v2** and **bge-large-en-v1.5** also perform well, while traditional retrieval methods like **BM25** remain competitive at Recall@10 but lag behind embedding-based methods at lower recall levels. **T5-base** and **BERT-based models** exhibit lower recall, suggesting that general pre-trained models are less effective for specialized memory retrieval. These results highlight **text-embed3-small** as the most effective choice for long-term memory activation in multi-session dialogues.

### C.2 Effectiveness of the Proactive Response Strategy

To better understand the impact of the proactive response strategy, we present a complementary analysis that examines two distinct metrics: slot accuracy measured during the confirmation phase and the final task success rate. Although these metrics reflect different aspects of system performance—localized slot-level correctness versus overall goal completion—they jointly capture the effectiveness of proactive correction.

As shown in Table 11, slot accuracy remains relatively low (ranging from 0.48 to 0.62) before correction, indicating frequent omission or mismatch in predicted slot values. Nevertheless, the final task success rates reach 0.87 or higher across all models after proactive correction is applied. This pattern suggests that the proactive response strategy plays a critical role in bridging the gap between partial slot-level understanding and complete task execution by enabling the system to recover from intermediate errors through user interaction.

### C.3 Human Evaluation Details

Table 15 presents the results of human evaluation, including accuracy, informativeness, and coherency scores. Accuracy is rated on a scale of 0 to 1, while

informativeness and coherency are rated from 0 to 3. The average scores in 5 are computed using a weighted sum with weights of 1, 1/3, and 1/3. All evaluations were conducted in a blind review manner to compare the response quality of w/o MAP and w/ MAP. Additionally, the Confirmation-type Response type assesses the response quality after memory-guided dialogue planning, while the multi-turn evaluation focuses on dialogues under the proactive response strategy, continuing until task completion or forced termination.

### C.4 Additional Evaluation Metrics

Table 13 compares the performance of task-oriented dialogue models with and without memory-augmented processing (MAP) across Slot Accuracy, BLEU, and ROUGE metrics. The results reveal a trade-off between structured slot accuracy and response fluency. In most models, MAP slightly reduces slot accuracy, as seen in LLaMA3-8B, which drops from 0.62 to 0.56, and Mistral-7B, which decreases from 0.59 to 0.56. However, GPT4o-mini benefits from MAP, achieving the highest slot accuracy of 0.68. BLEU scores generally decline, suggesting that MAP shifts responses away from verbatim accuracy towards greater contextual adaptability. Mistral-7B drops from 10.90 to 6.66, and LLaMA3-8B decreases from 10.47 to 9.86. Conversely, ROUGE scores improve with MAP in several cases. LLaMA3-8B increases from 28.59 to 30.39, and Qwen-7B rises from 29.77 to 31.28, indicating enhanced informativeness and coherence. However, Mistral-7B experiences a slight decrease in ROUGE from 28.42 to 24.64. Overall, the results suggest that MAP enhances response informativeness while slightly compromising slot accuracy and BLEU, highlighting a trade-off between structured information retention and more natural, contextually aware responses.

Table 14 presents the performance comparison between AutoTOD and MAP on Slot Accuracy, BLEU, and ROUGE. The results indicate that MAP consistently outperforms AutoTOD across all three metrics, demonstrating its effectiveness in enhancing dialogue quality. Slot Accuracy improves from 0.61 to 0.68, indicating better tracking of task-specific information. BLEU increases from 3.34 to 5.47, reflecting more precise and fluent responses. ROUGE also shows a slight improvement, rising from 24.07 to 25.03, suggesting that MAP enhances informativeness and coherence. These results highlight the advantages of memory-

Dimension	MultiWOZ	SGD
# Domains	7	20
Avg. Intents per Domain	8–10	10–15
Total Intents	~60	~200
Annotation Structure	Fixed, manually updated	Schema-driven, extensible
Cross-Domain Intent Interaction	Limited (2–3 domain combos)	Rich (multi-domain intent chains)

Table 10: Comparison between MultiWOZ and SGD datasets.

Model	Slot Acc. (Pre)	Task Rate (Post)
LLaMA3-8B	0.62	0.92
Qwen-7B	0.48	0.87
Mistral-7B	0.59	1.00
GPT4o-mini	0.61	0.99

Table 11: Effectiveness of the Proactive Response Strategy. Slot accuracy is measured before correction, and task rate reflects the final success after proactive clarification.

Activation Module	Recall@3	Recall@5	Recall@10
bm25	0.642	0.721	0.842
t5-base	0.443	0.575	0.773
bert-base	0.463	0.584	0.785
bert-large	0.401	0.530	0.730
nv-embed-v2	0.668	0.769	0.896
bge-large-en-v1.5	0.681	0.761	0.888
<b>text-embed3-small</b>	<b>0.702</b>	<b>0.792</b>	<b>0.905</b>

Table 12: Performance evaluation of activation modules on memory retrieval

Model	Setting	Slot Accuracy	BLEU	ROUGE
<b>LLaMA3-8B</b>	w/o MAP	<b>0.62</b>	<b>10.47</b>	28.59
	w/ MAP	0.56	9.86	<b>30.39</b>
<b>Qwen-7B</b>	w/o MAP	0.48	10.33	29.77
	w/ MAP	<b>0.55</b>	<b>10.90</b>	<b>31.28</b>
<b>Mistral-7B</b>	w/o MAP	0.59	<b>10.09</b>	<b>28.42</b>
	w/ MAP	<b>0.56</b>	6.66	24.64
<b>GPT4o-mini</b>	w/o MAP	0.61	<b>20.30</b>	<b>43.49</b>
	w/ MAP	<b>0.68</b>	13.6	35.20

Table 13: Performance comparison of task-oriented dialogue models with and without long-term memory integration: Slot Accuracy, BLEU, and ROUGE metrics.

Model	Slot Accuracy	BLEU	ROUGE
AutoTOD	0.61	3.34	24.07
MAP	<b>0.68</b>	<b>5.47</b>	<b>25.03</b>

Table 14: Performance comparison on Slot Accuracy, BLEU, and ROUGE.

augmented processing, which enables more accurate and contextually relevant dialogue generation.

## D Case Study Detail

### D.1 Multi-session Dialogue Context Comparison

Figure 14 presents four different configurations of conversation contexts not shown in the main paper. Specifically, (1) Full conversation history includes every session from the dialogue history as prompt input to the reader. (2) Retrieval-based methods retrieve the dialogue sessions most relevant to the current session (Session 23) and append them to the reader’s context (3) Retrieving a summary compiles a summary of past sessions (Sessions 1 to 22) for inclusion alongside the current context. Finally, (4) MAP integrates QA memory with the Session 23 context to generate responses. By illustrating these detailed contexts, Figure 14 provides further insights into how each approach manages multi-session dialogue.

### D.2 CoT+RAG vs. RAG

To better understand how CoT reasoning and memory reranking affect confirmation response generation, we present a step-by-step case study comparing CoT+RAG and standard RAG (Appendix Table 16). In this example, the user attempts to confirm a restaurant reservation. While both systems retrieve similar QA memory candidates, the standard RAG model fails to detect missing slot information (e.g., number of people), resulting in an incomplete and partially inaccurate response. In contrast, CoT+RAG explicitly identifies missing task information (e.g., time, headcount) through reasoning, refines the retrieved memories via the Memory Judger, and generates a more complete and contextually appropriate confirmation. This illustrates how structured reasoning and selective memory grounding improve slot coverage and reduce factual errors in multi-turn dialogue.

Model	Setting	Confirmation-type Response			Multi-Turn		
		Accuracy	Informativeness	Coherency	Accuracy	Informativeness	Coherency
GPT4o-mini	w/o MAP	0.62	1.83	1.90	0.81	1.92	2.44
	w/ MAP	<b>0.65</b>	<b>2.38</b>	<b>2.48</b>	<b>0.87</b>	<b>1.93</b>	<b>2.74</b>
LLaMA	w/o MAP	0.56	1.47	1.74	0.78	1.64	2.36
	w/ MAP	<b>0.61</b>	<b>1.98</b>	<b>2.16</b>	<b>0.88</b>	<b>2.51</b>	<b>2.71</b>
Qwen	w/o MAP	0.43	1.24	1.85	0.82	1.60	2.02
	w/ MAP	<b>0.54</b>	<b>1.70</b>	<b>2.30</b>	<b>0.92</b>	<b>1.93</b>	<b>2.47</b>
Mistral	w/o MAP	0.58	1.63	1.99	0.89	2.49	2.72
	w/ MAP	<b>0.61</b>	<b>2.06</b>	<b>2.08</b>	<b>0.93</b>	<b>2.74</b>	<b>2.85</b>

Table 15: Comparison of different models on human evaluation metrics: accuracy, informativeness, and coherence. The results are presented for both confirmation-type responses and multi-turn dialogue settings, comparing standard inference (‘w/o MAP’) with memory-augmented processing (‘w/ MAP’).

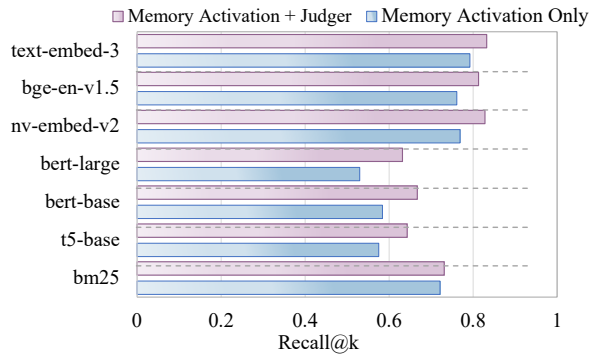


Figure 6: Impact of memory judger on memory activation performance across different embedding models.



## Prompts of the Dataset Generation

User Prompt:

"""

Help me generate an English conversation under the {dialogue\_intent} intent, where {task\_goal}. The conversation should be between a user and an assistant, and it should be split into {task\_goal\_length} sessions at different points in time, with continuity and connection between the sessions and each session should not less than 6 turns. Additionally, the final session must include a assistant response containing a complete confirmation-type utterance before the user confirms, and this utterance should be marked with 'is\_confirmation' set to 'True'. and the user must provide a final confirmation response at the end of the final session. For all other sessions, the conversation should end with an assistant's polite declarative statement.

"""

System Prompt:

""" You are dialogue generator assistant.

The sessions should be clearly separated, and the conversation should be formatted as follows:

Each turn should be a dictionary entry.

The conversation should be in the format of a list of sessions, where each session is a list of dictionaries representing each turn.

Each dictionary entry should have two keys: speaker (either 'user' or 'assistant') and text (the spoken dialogue).

Except for final session, each session should be a seperate dialogue and include a complete dialogue structure, beginning with a greeting from the user and ending with an assistant's polite declarative statement.

Feel free to expand the dialogue with additional relevant details, but avoid redundant expressions or repeating the same phrases.

Reponse me with a json format

```
{
  "sessions": [
    [
      {
        "speaker": "xx",
        "text": "xx"
      },
      {
        "speaker": "xx",
        "text": "xx"
      }
    ]
  ]
}
```

"""

Figure 7: Prompts of the Dataset Generation

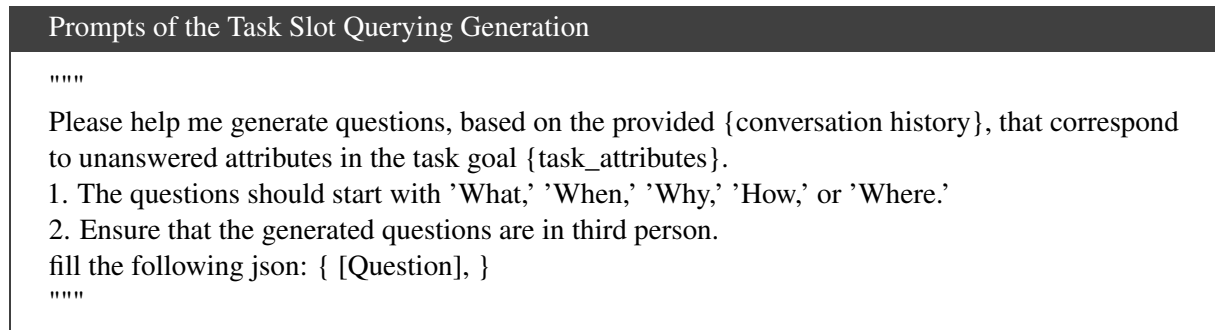


Figure 8: Prompts of the Task Slot Querying Generation

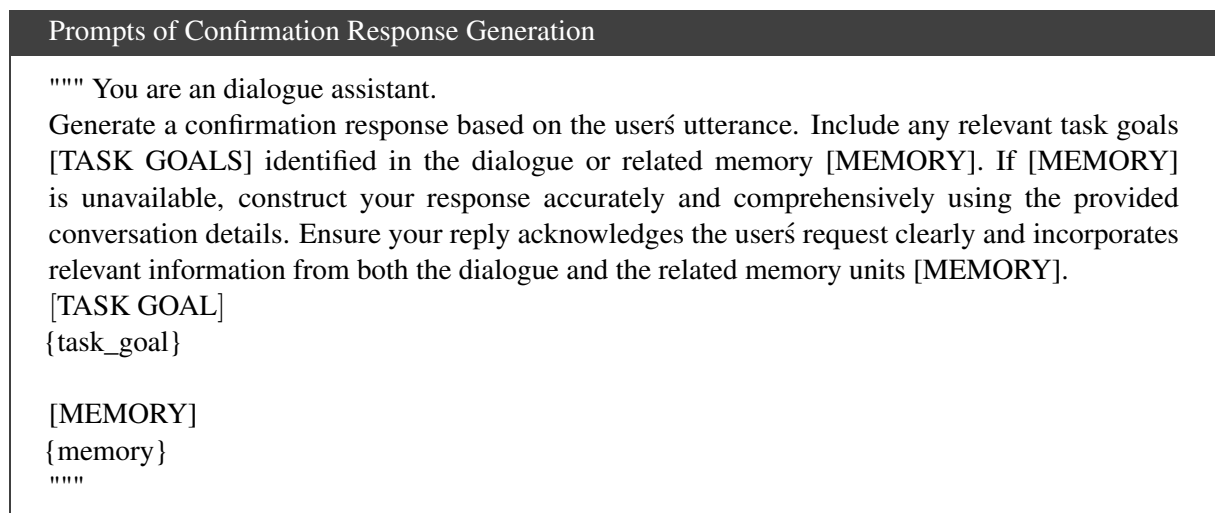


Figure 9: Prompt of Confirmation Response Generation

### Prompt of Dialogue State Tracking on MultiWOZ 2.2

""Consider the following list of concepts, called "slots" provided to you as a json list.

```
"slots": {  
  "attraction-area",  
  "attraction-name",  
  "attraction-type",  
  "bus-day",  
  "bus-departure",  
  "bus-destination",  
  "bus-leaveat",  
  "hospital-department",  
  "hotel-area",  
  "hotel-bookday",  
  "hotel-bookpeople",  
  "hotel-bookstay",  
  "hotel-internet",  
  "hotel-name",  
  "hotel-parking",  
  "hotel-pricerange",  
  "hotel-stars",  
  "hotel-type",  
  "restaurant-area",  
  "restaurant-bookday",  
  "restaurant-bookpeople",  
  "restaurant-booktime",  
  "restaurant-food",  
  "restaurant-name",  
  "restaurant-pricerange",  
  "taxi-arriveby",  
  "taxi-departure",  
  "taxi-destination",  
  "taxi-leaveat",  
  "train-arriveby",  
  "train-bookpeople",  
  "train-day",  
  "train-departure",  
  "train-destination",  
  "train-leaveat",  
}
```

Now consider the following dialogue between two parties called the "system" and "user". Can you tell me which of the "slots" were updated by the "user" in its latest response to the "system"? Present the updates in JSON format. If no "slots" were updated, return an empty JSON list. If you encounter "slots" that were requested by the "user" then fill them with "?". If the user informed that he did not care about a "slot", fill it with "dontcare". Return the output in JSON format and no explanation!

```
{ dialogue }  
""
```

Figure 10: Prompt of Dialogue State Tracking on MultiWOZ 2.2

### Prompts of GPT4 Evaluation

"" You are a strict and objective evaluator. Your task is to assess the quality of the final predicted response using the provided conversation context, the user's target goal attributes, and a reference answer. Your evaluation should be fair, professional, and reflect an expert judgment of the response's quality.

[Dialogue Context]

{{*conversation\_history*}}

[Task Goal]

{{*task\_goal*}}

[reference\_answer]

{{*reference\_answer*}}

[predict\_answer]

{{*predict\_answer*}}

Evaluation Criteria:

Requirement Alignment: Does the final predict\_answer meet the user's task goal?

Content Accuracy: Is the information in the final response correct, clear, and logically organized?

Language Quality: Is the language fluent, coherent, and readable? Are there any obvious grammatical or word choice errors?

Comparison to Reference Answer: Compared to the reference answer, how does the final response differ in terms of completeness, professionalism, and clarity?

Overall Score: Assign a score from 1 to 10 (10 being the best), considering all of the above factors.

The evaluation must be structured in the following JSON format:

““json

{

"Rationale": "<Explain the rationale of your score.>",

"Score": <An integer score from 1 to 10.>

}

““ """""

Figure 11: Prompts of GPT4 Evaluation



## MS-TOD dialogue session structure

```
{
  "session_id": 9,
  "domain": "Travel",
  "reference_dialogue_id": "66_00101",
  "exist_confirmation": true,
  "intent": "ReserveHotel",
  "content": [
    {
      "speaker": "user",
      "utterance": "Hi again, I'm ready to finalize the booking for Aloft Portland Airport At Cascade Station.",
      "is_confirmation": false
    },
    {
      "speaker": "assistant",
      "utterance": "Just to confirm, you are booking 1 room at Aloft Portland Airport At Cascade Station, Portland, from March 5th to March 7th. The room is a standard king room with free Wi-Fi and a 24-hour cancellation policy. Is that correct?",
      "is_confirmation": true
    },
    {
      "speaker": "user",
      "utterance": "Yes, that is correct.",
      "is_confirmation": false
    },
    {
      "speaker": "assistant",
      "utterance": "Excellent! Your room has been successfully booked. You will receive a confirmation email shortly.",
      "is_confirmation": false
    },
    {
      "speaker": "user",
      "utterance": "Thank you so much for your help!",
      "is_confirmation": false
    },
    {
      "speaker": "assistant",
      "utterance": "You're welcome! Have a great stay in Portland.",
      "is_confirmation": false
    }
  ],
  "task_goal": {
    "hotel_name": "Aloft Portland Airport At Cascade Station",
    "location": "Portland",
    "check_in_date": "March 5th",
    "check_out_date": "March 7th",
    "number_of_rooms": 1
  }
}
```

Figure 12: MS-TOD Session Structure.

## MS-TOD Intent Description and QA Memory

```
{
  "9": {
    "intent_description": "The user's intent is to finalize and confirm a
      hotel booking for a specific room at Aloft Portland Airport At Cascade
      Station, including details about the stay dates and room type.",
    "qa_summary": [
      {
        "Question": "What type of room did the user book?",
        "Answer": "The user booked a standard king room."
      },
      {
        "Question": "When is the user's reservation?",
        "Answer": "The user's reservation is from March 5th to March 7th."
      },
      {
        "Question": "Where is the user's reservation located?",
        "Answer": "The user's reservation is located at Aloft Portland Airport
          At Cascade Station."
      },
      {
        "Question": "What amenities are included in the user's reservation?",
        "Answer": "The user's reservation includes free Wi-Fi."
      },
      {
        "Question": "What is the cancellation policy for the user's booking?",
        "Answer": "The cancellation policy for the user's booking is 24 hours
          ."
      }
    ]
  }
}
```

Figure 13: Intent description and QA Memory in MT-TOD.

Process	CoT+RAG	RAG
Input and Intent		
Dialogue History	User: Have you completed the reservation at Gen Korean BBQ House?	User: Have you completed the reservation at Gen Korean BBQ House?
Intention Description	The user wants to confirm restaurant reservation.	The user wants to confirm restaurant reservation.
Memory Retrieval		
Retrieved QA Memory Candidates	<p><b>Rank 1:</b></p> <ul style="list-style-type: none"><li>Q: What is the time of the reservation? A: March 1st</li><li>Q: What is the address of the reservation? A: Los Angeles</li></ul> <p><b>Rank 2:</b></p> <ul style="list-style-type: none"><li>Q: What is the time of reservation? A: March 4th</li><li>Q: How many people are there? A: 2</li><li>Q: What is the address of the restaurant? A: Gen Korean BBQ House in Milpitas</li><li>Q: What is the time of reservation? A: March 1st</li><li>Q: What is the address of the restaurant? A: Gen Korean BBQ House in Milpitas</li></ul>	
CoT Reasoning		
Task Goal	Reserve Restaurant	—
Missing Slots	Time, Number of people	—
Missing Query	When is the time of reservation? How many people are there?	—
Memory Judger (Reranking)		
Reranked Memory Units	<ul style="list-style-type: none"><li>Q: What is the time of reservation? A: March 4th</li><li>Q: How many people are there? A: 2</li><li>Q: What is the address of the restaurant? A: Gen Korean BBQ House in Milpitas</li></ul>	Same as retrieved
Refinement-grounded Response Generation		
Confirmation Response	Just to confirm, it’s a reservation for 2 at Gen Korean BBQ House in Milpitas on March 4th at 12:15 pm, with a request for a quieter table. Is that correct?	To confirm, it’s a reservation for 2 at Gen Korean BBQ House Los Angeles on March 1st. Is that correct?

Table 16: Step-by-step comparison of MAP vs. standard RAG in confirmation response generation.

Session ID	Dialogue History	Summary	Intention-driven QA Memory
Session 1	User:Hi there! I'd like to book an appointment at Blow Dry Bar. Assistant : Sure! When would you like to schedule your appointment? ...	The user wants to book an appointment at Blow Dry Bar on March 3rd at 3:15 pm. The assistant confirms the date and is checking the availability for the requested time.	<b>Intention Description:</b> The user intends to book a specific appointment.  "Question": "What type of appointment is the user looking to book?", "Answer": "The user is looking to book an appointment at Blow Dry Bar." ...
Session 3	User:Hey, can you play the song 'Drive' on the <b>bedroom speaker</b> ? Assistant:Sure, I can play 'Drive' for you. Do you want me to start the song now? ...	The user requested to play the song \"Drive\" on the <b>bedroom</b> . The assistant confirmed and started the song, asking if the user needed anything else. The user declined further assistance and expressed gratitude.	<b>Intention Description:</b> The user intends to listen to the song.  "Question": "Where was the song 'Drive' played?", "Answer": "The song 'Drive' was played on the <b>bedroom speaker</b> ."
Session 12	User:Hi there! I'm interested in buying a ticket for the Bill Callahan concert? Assistant:Great choice! The Bill Callahan concert is happening on March 10th in Los Angeles. How many tickets would you like to purchase? ...	The user expresses interest in buying a ticket for the Bill Callahan concert on March 10th in Los Angeles. They request one ticket, and the assistant confirms availability and asks if the user would like to proceed with the purchase.	<b>Intention Description:</b> The user's intent is to purchase a single ticket  "Question": "Where will the concert be held?", "Answer": "The concert will be held in Los Angeles."
Session 16	User:Hi, I need to book a ride. Assistant:Sure, I can help with that. Where would you like to go? ...	The user wants to book a ride to 1580 Clayton Road #1 for three people and has requested a shared ride.	<b>Intention Description:</b> The user's intent is to arrange a shared transportation service.
Session 23 Evaluation	User: Can you play 'Drive' again? Assistant:		<b>Intention Guess:</b> The user intends to listen to songs.
Confirmation Response (Direct Prompting with the Full Conversation History)	Sure! Just to confirm, you'd like me to play the song "Drive" on the <b>bedroom speaker</b> again. Should I start it now? <i>Also, would you like me to check out some tickets for the Bill Callahan concert on March 10th in Los Angeles, or are you planning to book a ride somewhere else? Let me know! (Extra Noise)</i>		
Confirmation Response (Hybrid RAG with Retrieved History)	Sure! Let me play "Drive" for you once more. By the way, have you decided on the number of tickets you'd like to buy for Bill Callahan's concert? It's coming up on March 10th in Los Angeles! <i>(Wrong Answer)</i>		
Confirmation Response (Hybrid RAG with Summary)	Sure! I've started playing "Drive" again. Is there anything else you'd like? <i>(Wrong Answer)</i>		
Confirmation Response (MAP)	Sure! Just to confirm, you'd like me to play the song "Drive" on the <b>bedroom speaker</b> again. Should I start it now? <i>(Right Answer)</i>		

Figure 14: Comparison of confirmation response generation across four approaches: (1) Direct Prompting with the full conversation history, (2) Hybrid RAG retrieving relevant dialogue history, (3) Hybrid RAG retrieving a summary of the conversation, and (4) MAP with intention-based QA memory.