

THEANINE: Revisiting Memory Management in Long-term Conversations with Timeline-augmented Response Generation

Seo Hyun Kim^{1*} Kai Tzu-iunn Ong^{1*}
 Taeyoon Kwon^{1†} Namyung Kim^{1†} Keummin Ka^{1†} SeongHyeon Bae¹
 Yohan Jo² Seung-won Hwang² Dongha Lee¹ Jinyoung Yeo¹

¹Yonsei University, ²Seoul National University

Abstract

Large language models (LLMs) are capable of processing lengthy dialogue histories during prolonged interaction with users without additional memory modules; however, their responses tend to overlook or incorrectly recall information from the past. In this paper, we revisit memory-augmented response generation in the era of LLMs. While prior work focuses on getting rid of outdated memories, we argue that such memories can provide contextual cues that help dialogue systems understand the development of past events and, therefore, benefit response generation. We present **THEANINE**, a framework that augments LLMs’ response generation with memory timelines – series of memories that demonstrate the development and causality of relevant past events. Along with THEANINE, we introduce **TeaFarm**, a counterfactual-driven question-answering pipeline addressing the limitation of G-Eval in long-term conversations. Supplementary videos of our methods and the  TeaBag dataset for TeaFarm evaluation are in <https://theanine-693b0.web.app/>.

1 Introduction

Recently, the impressive performance of large language models (LLMs) has caused a trend of having longer conversations with them across multiple sessions (Fui-Hoon Nah et al., 2023). Such prolonged interactions require the models to memorize previous events or speaker information, tailoring the responses accordingly to keep up user interest (Adiwardana et al., 2020). While the large context windows of LLMs¹ allow them to process the entire dialogue history for response generation (RG), this often leads to biased attention toward the latest

*These two authors are the co-first authors and both have the right to list their names first on their CVs.

†T Kwon, N Kim, and K Ka are the co-second authors.

¹Recent LLMs, such as GPT-4 (Achiam et al., 2023) and LLaMA3 (MetaAI, 2024), have contexts windows of 128,000 and 1,040,000 tokens, respectively.

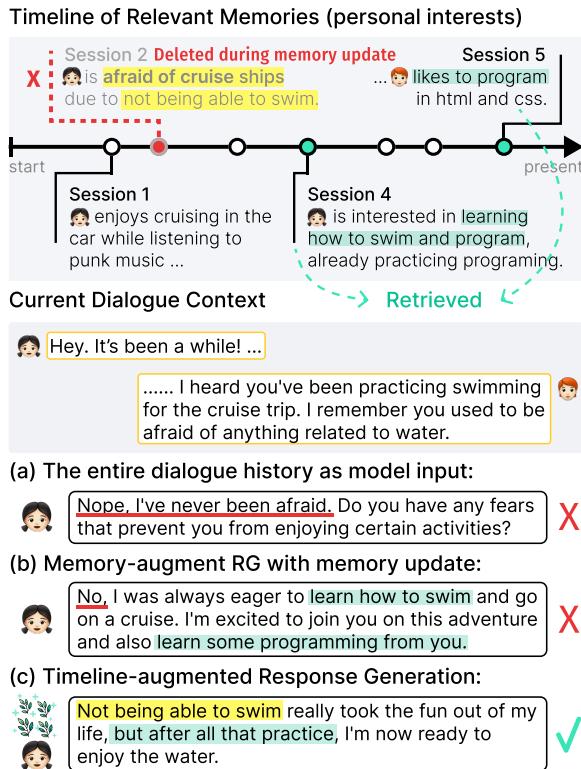


Figure 1: Empirical examples of failed responses due to (a) bias to the latest input (b) the absence of an important past event (“afraid of cruise ships”) on the timeline. (c) shows a response augmented with the memory timeline.

user utterance, ignoring relevant contexts from the past (Liu et al., 2024), as presented in Figure 1 (a).

One straightforward solution is to condense past conversations into summarized memories and retrieve them to augment response generation in later sessions (Xu et al., 2022a,b; Lu et al., 2023), but the growing span of memories can hinder the quality of memory retrieval as dialogue sessions accumulate. Although this can be mitigated by updating the older memories (Bae et al., 2022; Zhong et al., 2024; Kim et al., 2024a), we observe severe information loss. As illustrated in Figure 1 (b), an earlier memory on the timeline, which contains an important speaker persona (*i.e.*, “afraid of ships”),

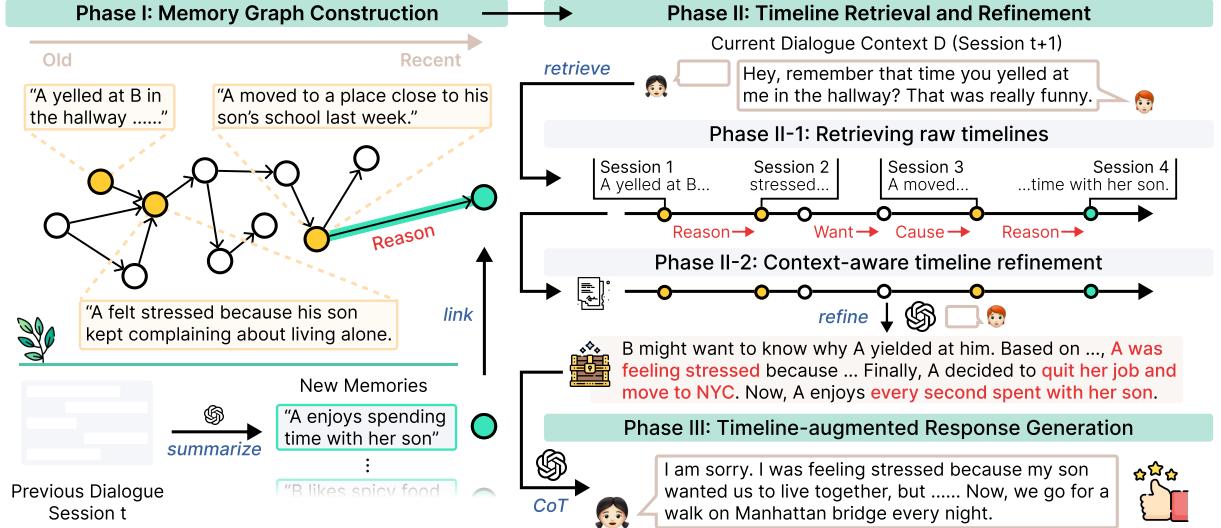


Figure 2: The overview of **THEANINE**. Left: Linking new memories to the memory graph after finishing a dialogue session; Right: Memory timeline retrieval, refinement, and response generation in a new dialogue session.

is removed during memory update (thus can not be retrieved), yielding a suboptimal response.

Motivated by these, in this paper, we revisit memory-augmented response generation for long-term conversations and address the aforementioned bottlenecks. Specifically, we focus on using the timeline built with relevant memories to augment response generation. To this end, we present **THEANINE**,² a framework of timeline-augmented chain-of-thought reasoning for response generation in long-term conversations.

Inspired by how humans naturally link new memories to existing memories of relevant events and retrieve them as a whole (Bartlett, 1995), THEANINE manages memories with a graph structure, *i.e.*, the memory graph, where memories are linked based on how they relate to each other (**Phase I**). Intuitively, this can be done by linking each memory to others that have high text similarity. Yet, we find this naive approach not much beneficial to response generation, due to the plain connection between memories (*e.g.*, “this happened → that occurred”). To resolve this, we leverage an LLM to dynamically link memories based on their temporal and cause-effect commonsense relations (Hwang et al., 2021) via our designed algorithm. Next, in memory retrieval for generating a new response (**Phase II-1**), instead of solely retrieving top- k memories using current conversation as query, we retrieve the whole memory timeline representing the development of relevant events. Then, to tackle the

²L-theanine is an amino acid found in green tea that has been linked to memory improvement (Nguyen et al., 2019).

discrepancy between off-line memory construction and online deployment (**Phase II-2**), THEANINE refines the retrieved timeline such that it provides tailored information for the current conversation. Finally, in response generation (**Phase III**), we leverage LLMs’ chain-of-thought (CoT) reasoning ability (Wei et al., 2022) to reason over current conversation and refined timelines, conclude useful information, and generate the final response. Our contributions are three-fold:

- We revisit memory-augmented response generation in long-term conversations with a novel timeline-augmented framework, **THEANINE**. In both LLM-based (*i.e.*, G-Eval) and human evaluation, THEANINE demonstrates (i) better responses that are detailed/non-generic and (ii) efficiency in properly referencing past conversations.
- The lack of ground-truth mapping between ongoing conversations (queries) and memories for retrieval poses a challenge in evaluating memory-augmented dialogue systems. We present **TeaFarm**, a counterfactual-driven question-answering pipeline, that assesses systems in referencing past conversations, which does not require human intervention.
- We further curate **TeaBag**, the counterfactual question-answer data for **TeaFarm** evaluation on two widely used benchmark datasets of long-term conversations: Multi-Session Chat (MSC) (Xu et al., 2022a) and Conversation Chronicles (CC) (Jang et al., 2023).

2 Methodologies

We present  THEANINE (Figure 2), a framework that resembles the mechanism of how humans store and retrieve memories for conversations:

2.1 Memory Graph Construction (Phase I)

To replicate how humans construct memories, we approach memory management based on a graph structure, *i.e.*, the memory graph G :

$$G = (V, E) \quad (1)$$

$$V = \{m_1, m_2, \dots, m_{|V|}\} \quad (2)$$

$$m = (\text{event}, \text{time}) \quad (3)$$

$$E = \{\langle m_i, r_{ij}, m_j \rangle | m_i, m_j \in V \wedge r_{ij} \in R\} \quad (4)$$

$$R = \{\text{Cause, Reason, Want, ..., SameTopic}\} \quad (5)$$

In G , vertices V are memories m summarized from the conversations. Each memory $m = (\text{event}, \text{time})$ consists of an event³ and the time it is formed (summarized). Each directed edge $e \in E$ between two connected m indicates their temporal order and their cause-effect commonsense relation $r \in R$:

At the end of dialogue session t ,  THEANINE starts linking each new memory m_{new} summarized from session t to the memory graph G^t .

Phase I-1: Identifying associative memories for memory linking. Following how humans link new memories to existing ones that are related to a similar event/topic, *i.e.*, the **associative memories**, THEANINE starts by identifying these associative memories from the memory graph G^t .

Formally, given a newly-formed memory m_{new} waiting to be stored, the associative memories M_a of m_{new} is defined as the set of $m_i \in G^t$ having top- j text similarity with m_{new} (*i.e.*, $|M_a| = j$).

Phase I-2: Relation-aware memory linking. Intuitively, we can link m_{new} to $m \in M_a$ using edges that indicate their text similarity and chronological order, we find such simplified connection (*e.g.*, “this happened → that similar event occurred”) can yield a context-poor graph that does not help response generation much (Section 4).

Humans, on the other hand, interpret events by considering the relation between them, such as “*how does an event affect the other?*” or “*why did this person make that change?*”

³In this work, “event” denotes information perceived by the dialogue system, including things done/said by speakers and the acknowledgement of speaker personas.

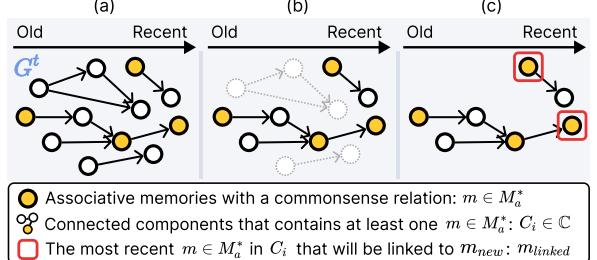


Figure 3: Locating memories to be linked to m_{new} .

Therefore, we adopt a relation-aware memory linking, where each edge between two memories is encoded with their cause-effect commonsense relation $r \in R$, along with their temporal order. These relations are adopted from Hwang et al. (2021) and modified by us, including HinderedBy, Cause, Want, and 4 more (Appendix A.1).

We start by determining the relation between m_{new} and each associative memory. Formally, for each pair of m_{new} and $m \in M_a$, the LLM assigns a relation $r \in R$ based on their *event, time* and their origin conversations:

$$M_a^* = \{m_i \in M_a | \Upsilon(m_i, m_{new}) \in R\} \quad (6)$$

where $\Upsilon(\cdot, m_{new}) \in R$ indicates that the given memory is assigned with an $r \in R$ with m_{new} ,⁴ and such assigned memories are defined as M_a^* .

We then proceed to link m_{new} to the graph, a straightforward approach is linking m_{new} to all $m \in M_a^*$. Yet, we find it algorithmically inefficient (Figure 7). Thus, we selectively link m_{new} to only those $m \in M_a^*$ that are recent. To identify those recent memories, we first locate every connected component $C_i \subset G^t$ that contains at least one $m \in M_a^*$, as shown in Figure 3 (a) and (b):

$$\mathbb{C} = \{C_i \subset G^t | V(C_i) \cap M_a^* \neq \emptyset\} \quad (7)$$

where \mathbb{C} is the collection of those C and $V(\cdot)$ represents “vertices in”. Now, we link m_{new} to the most recent $m \in M_a^*$ in each $C_i \subset \mathbb{C}$ (Figure 3 (c)). Therefore, the memories M_{linked} that are linked to m_{new} is defined as follows:

$$M_{linked} = \{\Omega(V(C_i) \cap M_a^*) | C_i \subset \mathbb{C}\} \quad (8)$$

where $\Omega(\cdot)$ indicates “the most recent memory in”. Linking all memories from session t to G^t , we then obtain a new memory graph G^{t+1} . The pseudo algorithm for Phase I is in **Algorithm 1**.

⁴Limited by the performance of retrievers, it is possible that an $m \in M_a$ does not have a relation, other than just textual overlap, with m_{new} . We address this by allowing the LLM to output “None”.

2.2 Timeline Retrieval and Timeline Refinement (Phase II)

Drawing motivation from Figure 1, THEANINE augments response generation (RG) with timelines of relevant events to address the information loss caused by conventional memory management (Xu et al., 2022a; Bae et al., 2022). With G^{t+1} , THEANINE performs these steps for RG in session $t + 1$:

Preparation: Top- k memory retrieval. During the conversation, using the current dialogue context $\mathcal{D} = \{u_i\}_{i=1}^n$ of n utterances u as query, we first retrieve top- k memories $M_{re} = \{m_{re1}, \dots, m_{rek}\}$.

Phase II-1: Retrieving raw memory timelines.

After that, we wish to also access memories that are centered around relevant events. Formally, given an $m_{re} \in M_{re}$, we further retrieve the connected component $C_{re} \subset G^{t+1}$ that contains m_{re} .

Since this collection of memories (*i.e.*, C_{re}) can be “tangled up” together (*i.e.*, connected in a complex manner) due to the graph structure, we proceed to untangle it into several memory timelines, each representing a series of events about m_{re} that starts out similarly yet branches into slightly different development. For that, we first locate the earliest memory in C_{re} as a starting point m_{start} for all timelines, as shown in Figure 4 (left).

$$m_{start} = \Theta(V(C_{re})) \quad (9)$$

where Θ indicates “the oldest memory in”

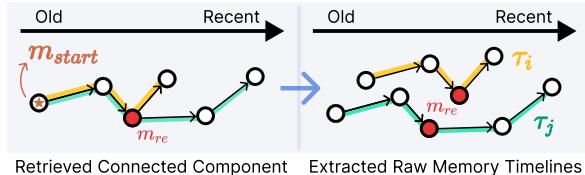


Figure 4: Extracting raw memory timelines τ from the retrieved connected component C_{re} .

Next, starting from m_{start} , we untangle the memories by tracing through the future direction and extract every possible linear graph containing m_{re} (two in Figure 4) from C_{re} , until reaching an endpoint $\tau[-1]$ with an out-degree of 0 (*i.e.*, $\deg^+(\tau[-1]) = 0$, which means no directed edge goes out from it). Each of them is considered a raw memory timeline τ , demonstrating a version of the evolution of m_{re} and its relevant events:

$$\begin{aligned} \mathcal{T} = \{ &\tau \subset C_{re} \mid \tau \text{ is a directed linear} \\ &\text{graph s.t. } m_{start}, m_{re} \in \tau \\ &\wedge \deg^+(\tau[-1]) = 0 \} \end{aligned} \quad (10)$$

We then sample n raw timelines τ from \mathcal{T} .⁵ Repeating Phase II-1 for all retrieved top- k memories, we collect a set of retrieved raw memory timelines $\mathbb{T} = \cup \mathcal{T}$, where $|\mathbb{T}| = k^* n$.

Phase II-2: Context-aware timeline refinement. Although we have constructed the memory graph using temporal and commonsense relations to improve its informativeness, directly applying the retrieved timelines for response generation can be suboptimal (RQ3, Section 4), because graph construction does not take the current conversation into consideration, *i.e.*, they are constructed *off-line*.

In this phase, THEANINE tackles such a discrepancy between off-line memory construction and online deployment (*i.e.*, an ongoing current conversation) via a context-aware timeline refinement. Motivated how LLMs can self-refine their previous generation (Madaan et al., 2024). We leverage LLMs to refine raw timelines into a rich resource of information crafted for the current conversation, by removing redundant information or highlighting information that can come in handy. Formally, given the current dialogue \mathcal{D} and the retrieved raw memory timelines \mathbb{T} , the LLM tailors all $\tau \in \mathbb{T}$ into refined timelines \mathbb{T}_Φ :

$$\mathbb{T}_\Phi = \{\underset{\tau_\Phi}{\operatorname{argmax}} P_{LLM}(\tau_\Phi | \mathcal{D}, \tau) \mid \tau \in \mathbb{T}\} \quad (11)$$

All refined timelines \mathbb{T}_Φ are then used to augment the response generation. We provide the pseudo algorithm for Phase II in [Algorithm 2](#).

2.3 Timeline-augmented Response Generation (Phase III)

Finally, we move on to response generation. Here, THEANINE leverages LLMs’ chain-of-thought (CoT) reasoning to discover user intention from the current conversation (Chae et al., 2023) and selectively extract useful information provided in the refined timelines. Formally, given the current dialogue context $\mathcal{D} = \{u_i\}_{i=1}^n$ and refined timelines \mathbb{T}_Φ , the LLM sequentially generates a CoT rationale \mathcal{R} demonstrating how it comprehends \mathcal{D} and \mathbb{T}_Φ , and the next response \bar{u}_{t+1} :

$$\bar{\mathcal{R}} = \underset{\mathcal{R}}{\operatorname{argmax}} P_{LLM}(\mathcal{R} | \mathcal{D}, \mathbb{T}_\Phi) \quad (12)$$

$$\Rightarrow \bar{u}_{n+1} = \underset{u_{n+1}}{\operatorname{argmax}} P_{LLM}(u_{n+1} | \mathcal{D}, \mathbb{T}_\Phi, \bar{\mathcal{R}}) \quad (13)$$

where \Rightarrow denotes sequential text generation.

⁵Based on our experiments, we empirically set n to 1.

3 Experimental Setups

3.1 Datasets of Long-term Conversations

There are few datasets of long-term conversations. First, Multi-Session Chat (MSC) (Xu et al., 2022a), which is built upon the conversations from Persona-Chat (Zhang et al., 2018) by extending their follow-up conversations throughout multiple sessions. Soon after MSC, DuLeMon (Xu et al., 2022b) and CareCall (Bae et al., 2022) are proposed for long-term conversations in Mandarin and Korean, respectively. Recently, Jang et al. (2023) release a new multi-session datasets, Conversation Chronicles (CC). Different from MSC, speakers in CC are augmented with diverse relationships, such as “*employee and boss*”. Apart from the above open-domain datasets, there is also Psychological QA,⁶ which addresses long-term conversation in Mandarin regarding clinical scenarios.

In this work, we adopt MSC and CC for evaluation. Since we focus on English conversations, we do not include DuleMon, CareCall, and Psychological QA. We leave such multilingual settings and clinical scenarios to future work.

3.2 Baselines

To evaluate THEANINE in long-term conversation, besides naive settings using all past dialogues or memories, we include the following baselines.

Memory retrieval. Following Xu et al. (2022a) and Xu et al. (2022b), this setting uses a retriever to retrieve memories with the current dialogue context to augment response generation.

+ Memory update. We use LLMs to perform the memory updating mechanism developed by Bae et al. (2022) to update the memory pool at the end of each session to enhance the above baselines.

RSum-LLM. Proposed by Wang et al. (2023), it uses an LLM to (i) recursively summarize and update the memory pool at the end of each session, (ii) select top memories based on the current dialogue, and (iii) generate responses.

MemoChat. Proposed by Lu et al. (2023), it uses LLMs’ CoT reasoning ability to (i) conclude important memories from past conversations in a structured topic-summary-dialogue manner, (ii) select memories, and (ii) generate responses.

COMEDY. Proposed by Chen et al. (2024b), rather than memory retrieval, it first summarizes session-level past summaries and then compresses all of

them into short sentences of events, user portraits (behavior patterns, emotion, etc.) and user-bot relation, using them to augment response generation.

3.3 Models and Implementation Details

Large language models. In all experiments including baselines, we adopt ChatGPT (gpt-3.5-turbo-0125) from OpenAI (2023) for (i) memory summarization, (ii) memory update, and (iii) response generation. We set the temperature to 0.75.

Retrievers. We use text-embedding-3-small (OpenAI, 2024b) from OpenAI to calculate the similarity of texts. For the identification of top- j associative memories (Phase I-1) and top- k memory retrieval (Phase II Preparation), we set j and k to 3. For the “Memory Retrieval” baseline, we retrieve 6 memories following Xu et al. (2022a).

Dialogue sessions. We perform evaluation using sessions 3-5 from both datasets, as all settings are almost identical before the end of session 2 (there is no memory to update before then).

4 Evaluation Scheme 1: Machine and Human Evaluation

To evaluate THEANINE, we first start with G-Eval (Liu et al., 2023), an LLM-based framework for assessing LMs’ responses, and human evaluation.⁷ Here, we focus on the following research questions (RQs):

RQ1. *Can THEANINE generate context-rich responses, rather than those generic and plain?*

RQ2. *Can THEANINE reference past conversations better than other methods?*

RQ3. *Do phases in THEANINE make sense?*

RQ4. *Do humans agree with THEANINE’s procedures, and how do they think of the final responses?*

THEANINE yields responses that are more detail-rich (RQ1).

In Table 1, we first assess whether generated responses are detail-rich, rather than generic and plain, *i.e.*, specificity (Spe). In both datasets, THEANINE yields significantly high win rates in the head-to-head comparison with all baselines except for RSum-LLM. We presume it is due to the fact that RSum-LLM tends to generate much longer responses (avg. 77 words per response) than other settings (ours = 32 words; avg of other baselines = 30 words).

⁷Details for G-Eval and human evaluation are in Appendix D and F. Dataset-specific results are in Appendix E.

⁶<https://www.xinli001.com/>

Datasets:		MULTI-SESSION CHAT (MSC) & CONVERSATION CHRONICLES (CC)											
Dialogue Session:		Session 3			Session 4			Session 5			Avg.		
 THEANINE		THEANINE's Winning Percentage											
vs.	Spe	Mem	Cst	Spe	Mem	Cst	Spe	Mem	Cst		Spe	Mem	Cst
All Dialogue History	71%	82%	77%	73%	81%	77%	72%	79%	77%		72%	81%	77%
All Memories and \mathcal{D}	69%	64%	66%	69%	69%	68%	70%	68%	68%		69%	67%	67%
+ Memory Update	56%	57%	60%	56%	56%	58%	56%	58%	60%		56%	57%	60%
Memory Retrieval	67%	62%	68%	72%	67%	68%	72%	65%	68%		70%	65%	68%
+ Memory Update	57%	56%	59%	58%	57%	61%	55%	58%	59%		57%	57%	60%
RSum-LLM	38%	61%	69%	35%	57%	67%	37%	57%	65%		37%	58%	67%
MemoChat	60%	74%	71%	60%	69%	72%	60%	72%	71%		60%	72%	71%
COMEDY	66%	54%*	78%	64%	54%*	77%	62%	53%*	76%		64%	53%	77%
Golden Responses	63%	76%	61%	63%	73%	61%	62%	72%	61%		63%	73%	61%

Table 1: **Win rates of THEANINE** in head-to-head G-Eval (of all generated responses) with baselines. Spe = specificity; Mem = memorability; Cst = consistency. **Color green** denotes metrics regarding the reference of memories. **Color gray** shows where ours loses more. Underline: p-value < 0.001. *: 0.001 < p-value < 0.05.

 **THEANINE utilizes past memories efficiently and correctly (RQ2).** In long-term conversations, it is crucial and necessary to further assess (i) whether the dialogue system utilizes information from the past when necessary (*i.e.*, memorability) and make sure (ii) the response does not contradict previous conversations (*i.e.*, consistency). We present the results in Table 1. THEANINE demonstrates high win rates in the comparisons with baselines. However, COMEDY performs almost as well as us regarding memorability, which we assume is because it always applies two additional LLMs to extract and compress past conversations into concise memos before each response generation (no retrieval). However, as we expected, always referencing concise and recent user information can lead to contradiction to older information, thus clearly beaten by THEANINE in terms of consistency (Cst).

Ablation results: Phases in  THEANINE matter (RQ3). Table 2 presents the results where key phases in THEANINE are removed. We observe that the removal of relation-aware memory linking (Phase I-2) and context-aware timeline refinement (Phase II-2) leads to large performance drops regarding the reference of past information (*i.e.*, the original THEANINE shows higher win rates), especially when timeline refinement is absent.

This justifies our methodological designs: (i) In graph construction, linking memories with cause-effect relation benefits RG more than naive connection using only text similarity and chronological order; (ii) By further refining memories built off-line (*i.e.*, without considering current conversations) before RG, we can elicit contextual cues that

MULTI-SESSION CHAT (Session 3-5)			
 THEANINE		Ours' Win Rate	
vs.	Mem	Cst	Avg.
w/o Relation-aware Linking	62%	65%	64%
w/o Timeline Refinement	62%	69%	65%
CONVERSATION CHRONICLES (Session 3-5)			
w/o Relation-aware Linking	60%	65%	63%
w/o Timeline Refinement	64%	68%	66%

Table 2: Ablation results (p-values < 0.001).

	Agree	Disagree
Appropriateness (Memory Linking)	92%	8%
Helpfulness (Timeline Refinement)	100%	
Responses & Past Conversations	34%	57% 9%

Entail Neutral Contradict

Figure 5: Results of human evaluation.

are tailored for the current conversation.

Humans think  THEANINE makes sense and properly references past conversations. As reported in Figure 5, human judges largely agree (92%) that THEANINE’s relation-aware memory linking is performed appropriately, and they all agree (100%) that timeline refinement can elicit more helpful/tailored information for response generation. Most importantly, THEANINE produces responses that either entail (*i.e.*, faithfully reflect) past conversations (34%) or, at worse, neutral statements (57%) in 91% of the cases from human standpoints, manifesting its’ efficacy in referencing past information in long-term conversations.

Examples of  THEANINE in terms of each phase are in Appendix G.

5 Evaluation Scheme 2: TeaFarm – a Counterfactual-driven Evaluation Pipeline for Long-term Conversations

Despite the success of G-Eval (Liu et al., 2023) in evaluating responses of LMs, accessing dialogue systems’ ability to utilize past memories in long-term conversation still remains challenging. This is due to the unavailability of ground-truth mapping between current conversations and the correct memories for retrieval. Although we can resolve this by feeding the evaluator LLM (*e.g.*, GPT-4) the entire memory pool or past history and prompt it to determine whether a response correctly recalls past conversations, the evaluation can be limited by the performance of the evaluator LLM itself.

To overcome this, along with THEANINE, we present TeaFarm, a counterfactual-driven pipeline for evaluating memory-augmented response generation in long-term conversations.

5.1 Testing Dialogue Systems’ Memory via Counterfactual Questions

In TeaFarm, we proceed to “trick” the dialogue systems into generating incorrect responses, and the system must correctly reference past conversations to avoid being misled by us. Specifically, we talk to the dialogue system while *acting as if a non-factual statement is true* (thus counterfactual). Figure 6 presents some examples of counterfactual questions and the corresponding facts.

Facts (at this moment)	Counterfactual Questions
Speaker B has never been to Japan.	A: Hey, did you have a great time in Tokyo?
Speaker A bought a new house in NYC three months ago.	B: So you are still hesitating to buy that house in NYC you’ve been talking about, right?
Speaker A does not sing and does not own a car.	B: I recall you saying you used to sing at your mom’s coffee shop, where is it?
Speaker B does not own a car.	B: Hey, do you remember when we sang karaoke in my car?

Figure 6: Examples of counterfactual questions.

In practice, when we want to evaluate a system that has been interacting with the user for multiple sessions, we first (1) collect all past conversations and summarize them session by session. Then, we (2) feed the LLM⁸ the collected summaries in chronological order such that it can capture the current stage of each discussed event, *e.g.*, “Speaker B has never been to Japan at this moment”, and

⁸We apply GPT-4 (gpt-4) with a temperature of 0.75.

(3) generate counterfactual questions from the perspective of both speakers (and the correct answers). After that, we (4) kick off a new conversation, chat for a while, then (5) naturally ask the counterfactual question, and (6) assess the correctness of its response. Overview illustration and prompts for TeaFarm are in Appendix B and H.

5.2 TeaFarm Results

Settings / Datasets	MSC	CC	Avg.
Memory Retrieval	0.16	0.19	0.18
+ Memory Update	0.16	0.19	0.18
RSum-LLM	0.04	0.08	0.06
MemoChat	0.09	0.15	0.12
COMEDY	0.06	0.18	0.12
 THEANINE	0.17	0.24	0.21
w/o Relation-aware Linking	0.06	0.13	0.10
w/o Timeline Refinement	0.15	0.16	0.16

Table 3: TeaFarm results regarding correct/total percentages of model responses. Tested in conversations from MSC and CC with 200 counterfactual questions.

In Table 3, we present model performance in TeaFarm evaluations. THEANINE outperforms all baselines, especially in CC. Ablations perform worse than original THEANINE, again proving the efficacy and necessity of relation-aware linking and timeline refinement. Surprisingly, all settings result in low correct rates, qualifying TeaFarm as a proper challenge for stress-testing dialogue systems in long-term conversations.

Interestingly, baselines that utilize retrievers (just like THEANINE) show superior performance than those relying on LLMs for memory selection (*i.e.*, RSum-LLM, MemoChat, and COMEDY).⁹ This pattern, unexpectedly, supports our idea of revisiting memory retrieval in the era of LLMs.

5.3 Dataset for TeaFarm: TeaBag

As a byproduct of TeaFarm, we curate  TeaBag, a dataset for TeaFarm evaluation on MSC and CC. TeaBag consists of (1) 100 episodes of original conversations from MSC and CC (session 1-5), (2) follow-up conversations (session 6), where the speaker will naturally converse toward the counterfactual questions, and (3) the corresponding answers. TeaBag serve as a useful tool for stress-testing if a system can correctly reference past conversations. Dataset details are in Appendix C.

⁹Memory update does not affect Memory Retrieval’s performance. We believe it is because the counterfactual questions are made to counter the newest stage of each event. The removal of older memories thus does not have much impact.

6 Further Discussions

Cost efficiency. In Phase I-2, we choose to link m_{new} to only the most recent associative memories in each C_i , rather than all associative memories in M_a . Figure 7 compares THEANINE with THEANINE-ALL, where m_{new} is linked to all $m \in M_a$. We find that although THEANINE-ALL costs 25% more, it is beaten by original THEANINE. We believe this is because linking m_{new} to all M_a leads to more short timelines (e.g., an m_{new} from session 4 is directly linked to an old memory from session 1), which provide less information than timelines built with relevant memories from more sessions. Regardless, it still yields lower loss rates than strong baselines. An open question here is whether we can reach a balance between cost and performance. We presume we can further improve the cost efficiency of THEANINE in the long-term by training a memory linker using the collected memory-relation pairs from LLMs via knowledge distillation. We leave it to future work.

Growing span of memories. Another inquiry left might be whether the growing span of memory would hinder memory retrieval in THEANINE if there ever were hundreds of sessions. Although this can be a serious issue for conventional memory retrieval, we argue that it will be much mitigated in THEANINE because: (i) We retrieve relevant memories *as a whole* in the form of timelines. This works as a safety net in scenarios where an important memory is missed out in top- k retrieval – it might still be retrieved along with the timeline; (ii) We perform timeline refinements. Similarly, this also acts as a second insurance against mis-retrieved memories that are actually not helpful.

API Cost for Linking	THEANINE	THEANINE's Win Rate			
		vs.	Spe	Mem	Cst
THEANINE:	1	THEANINE-ALL	67%	58%	66%
		RSum-LLM	37%	58%	67%
		MemoChat	60%	72%	71%
		COMEDY	64%	53%	77%

Figure 7: API cost and G-Eval results. Red shows baselines that **lose even more** than THEANINE-ALL in the head-to-head comparisons with original THEANINE.

7 Related Work

Long-term Conversations. Since the release of MSC (Xu et al., 2022a), there have been many studies on long-term conversations. For instance, Bae et al. (2022) train a classifier as the memory updaters to handle outdated memories in phone call

scenarios. Recently, based on LLMs’ outstanding in-context learning ability, Wang et al. (2023) leverage LLMs to write, update, and select memories for response generation. Apart from LLMs’ power, human behaviors have also fostered methods for long-term conversations. For example, Zhong et al. (2024) apply humans’ forgetting curve to make memories that have been discussed stay in the memory pool for a longer time. Also drawing inspiration from how humans manage memories, our THEANINE, on the other hand, addresses the connection between relevant events in both memory construction and retrieval, improving response quality in long-term conversations, which has never been explored to the best of our knowledge.

Memory-augmentation for personalized dialogue systems. The trend of long-term interaction with dialogue systems promotes the adaptation of them for personalized needs (Chen et al., 2024a,c). As a pioneer, Xu et al. (2022b) train a persona extractor to create user-based memories in long-term conversations. However, training a personalized system for long-term use can be non-trivial due to the lack of data (Tseng et al., 2024). As a solution, Kim et al. (2024a) apply commonsense models and LLMs to augment existing long-term conversation datasets with high-quality persona sentences; Chen et al. (2024b) present a training-free LLM-based framework that extracts user behaviors from past conversations for personalized responses. Upon the success of LLMs, THEANINE leverages them to build memory timelines, which represent the development of user personas/behaviors throughout the interaction, providing rich cues for personalized responses.

8 Conclusions

This work revisits memory management in multi-session/long-term conversations in the era of LLMs. Following how humans store and retrieve relevant memories as a whole, we present THEANINE, a framework of timeline-augmented response generation, which elicits responses that are detail-rich and, more importantly, able to correctly reference previous conversations when necessary. We also propose a novel evaluation pipeline (TeaFarm) that addresses the limitation of G-Eval in long-term conversations as well as the dataset for it (TeaBag). We expect this paper to serve as a groundwork and inspiration for exploring more paradigms of memory construction/retrieval in dialogue systems.

9 Limitations

This work has the following limitations: First, the maximum amount of dialogue sessions in this study is limited to five due to the lack of longer open-domain English datasets of multi-session conversations. Hence, THEANINE’s performance in longer conversations has not been investigated. As we mentioned in Section 6, we presume that its’ effectiveness can still hold true to some degree even in such scenarios. Yet, we do acknowledge the need to apply additional modules that directly address the growing span of dialogue history/memories. One possible way is to introduce the summarize-then-compress paradigm in COMEDY (Chen et al., 2024b) to THEANINE, which further compresses session-level summaries into a combined short user/event description.

Second, retrieving and refining timelines for response generation can be less computationally efficient than conventional memory retrieval, as there might exist scenarios where timelines are not necessary, *e.g.*, when there is no need to reference past conversations. We believe this can be mitigated by incorporating an additional selection logic/module to choose between memory retrieval, timeline retrieval, and no retrieval at all.

Lastly, although we include many recent frameworks as baselines, we failed to compare THEANINE with MemoryBank (Zhong et al., 2024), a framework inspired by Ebbinghaus’s forgetting curve. This is because the time intervals between sessions in MSC and CC are either mostly measured in hours or not clearly specified (*e.g.*, “a few months later”), whereas MemoryBank requires precise time intervals in days to apply the forgetting curve. Also, data used for MemoryBank focuses on Chinese clinical scenarios, making it not feasible for our study. However, we remain positive about applying such a mechanism to improve THEANINE in our ongoing research.

10 Ethical Statements

LLMs might generate harmful, biased, offensive, sexual content. Authors avoid such content from appearing in this paper. We guarantee fair compensation for human evaluators from Amazon Mechanical Turk. We ensure an effective pay rate higher than 20\$ per hour based on the estimated time required to complete the tasks.

11 Acknowledgments

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A Further Implementation Details

A.1 Cause-effect Commonsense Relations

We adopt and modify commonsense relations from [Hwang et al. \(2021\)](#) for our relation-aware memory linking. Below is the list of our commonsense relations R :

Changed: Events in A changed to events in B.

Cause: Events in A caused events in B.

Reason: Events in A are due to events in B.

HinderedBy: When events in B can be hindered by events in A, and vice versa.

React: When, as a result of events in A, the subject feels as mentioned in B.

Want: When, as a result of events in A, the subject wants events in B to happen.

SameTopic: When the specific topic addressed in A is also discussed in B.

Limited by the performance of retrievers, it is possible that an $m \in M_a$ does not have a relation, other than just textual overlap, with m_{new} . We address this by allowing the LLM to output **None**.

A.2 Algorithms for THEANINE

The pseudo algorithms for Phase I and II are provided in Algorithm 1 and 2.

A.3 Computational Experiments

All computational experiments in this work are based on OpenAI API ([OpenAI, 2024a](#)). Thus, no computing infrastructure is required in this work.

B TeaFarm Evaluation

The overview of **TeaFarm** is illustrated in Figure 8.

C The TeaBag Dataset

We curate  **TeaBag**, a dataset for **TeaFarm** evaluation on MSC and CC. TeaBag consists of:

- 100 episodes of original conversations from Multi-Session Chat and Conversational Chronicles (session 1-5; 50 episodes from each dataset)
- Two pairs of counterfactual QAs for each episode (200 pairs in total).
- Two synthesized session 6 for each episode (thus 200 in total), each of which naturally leads to one of the counterfactual questions.

This dataset is made with GPT-4. The prompt for generation is in Appendix H. We expect future

work to apply TeaBag to stress-test if their dialogue system can correctly reference past conversations.

TeaBag does not contain personally identifying information, as it is generated based on datasets where all contents are pure artificial creation, rather than contents collected from the real-world. Also, we have tried our best to confirm that this dataset does not contain any offensive content.

D G-Eval

G-Eval ([Liu et al., 2023](#)) is a framework using LLMs with chain-of-thoughts (CoT) and a form-filling paradigm, to assess the quality of models' text generation. G-Eval with GPT-4 has been shown to generate evaluation results that highly align with human judgement ([Liu et al., 2023](#); [Kim et al., 2024b](#)). Due to the high API cost for it, we conduct head-to-head comparisons between THEANINE and 8 baselines using 100 episodes from MSC and CC (around 3,600 THEANINE's responses being compared in each comparison with one baseline), rather than the whole test sets. The prompts for G-Eval are in Figure 20, 21, and 22. We use SciPy to calculate p-values.¹⁰

E Dataset-Specific G-Eval Results

We provide dataset-specific results of G-Eval in Table 4 and 5.

F Human Evaluation

We conduct human evaluation, with workers from Amazon Mechanical Turk (AMT). We construct the following three evaluations:

- **Appropriateness of relation-aware memory linking:** In this evaluation, we ask the workers to judge whether they agree that the relation-aware linking is properly done for two given memories.
- **Helpfulness of context-aware timeline refinement:** This evaluation requires the workers to determine if they agree that our context-aware refinement really tailors a raw timeline into a resource of useful information for generating the next response.
- **The quality of THEANINE's responses:** Here, the workers are asked to judge if the responses of THEANINE correctly refer to past conversations. After reading our responses

¹⁰<https://scipy.org/>

and past memories, they choose whether the responses entail, contradict, or are neutral to past memories. To improve evaluation quality, we use GPT-4 to select responses for this specific evaluation based on past memories, addressing the fact that not every turn in the conversation requires previous information to generate the next response (In the other two evaluations, the samples are randomly selected).

Each data sample is judged by 3 different workers, and we report the results based on the majority rule. In the third evaluation, when every option (entailment, neutral, contradiction) gets one vote, we consider it neutral (13 samples in total). These human evaluations are conducted on 300 samples. The interfaces provided to AMT workers, which include detailed instructions for human evaluation, are shown in Figure 9, 10, and 11.

G Empirical Examples

We provide several empirical examples of  THEANINE. Examples of relation-aware memory linking are in Figure 12, 13, and 14. Examples of utilizing refined timeline for response generation are in Figure 15.

H Prompts

The following are all prompts utilized in our study:

- Relation-aware memory linking (Phase I-2): Figure 16.
- Context-aware timeline refinement (Phase II-2): Figure 17.
- Timeline-augmented Response generation (Phase III): Figure 18.
- + Memory update (baseline): Figure 19.
- RSum-LLM (baseline): We adopt the original prompt from Wang et al. (2023).
- MemoChat (baseline): We adopt the original prompt from Lu et al. (2023).
- COMEDY (baseline): We adopt the original prompt from Chen et al. (2024b).
- G-Eval: Figure 20, 21, and 22.
- Generating counterfactual QA in TeaFarm: Figure 23.

- Generating session 6 in TeaFarm: Figure 24.
- Evaluating model responses in TeaFarm: Figure 25.

I Terms for Use of Artifacts

We adopt the MSC and CC datasets from Xu et al. (2022a) and Jang et al. (2023), respectively. Both of these datasets are open-sourced for academic and non-commercial use. Our curated dataset, TeaBag, which will be released after acceptance, is open to academic and non-commercial use.

Algorithm 1 Memory Graph Construction (Phase I)

Require: Memory graph $G^t = (V^t, E^t)$
Require: New memories $M_{new} = \{m_{new1}, \dots, m_{newN}\}$
Require: Set of relations $R = \{\text{Cause}, \text{Reason}, \text{Want}, \dots, \text{SameTopic}\}$
Ensure: Memory graph $G^{t+1} = (V^{t+1}, E^{t+1})$

- 1: $\Upsilon(m_i, m_j) = \begin{cases} r_{i,j}, & \text{if } m_i \text{ is assigned with } r_{i,j} \in R \text{ with } m_j \\ \text{None}, & \text{otherwise} \end{cases}$
- 2: $\Omega(V) = (\text{the most recent memory } m \in V)$
- 3: $E_{t+1} \leftarrow E_t$
- 4: **for** $m_{new} \in M_{new}$ **do**
- 5: $M_a \leftarrow \{m_i \in V^t \mid m_i \text{ has top-}j \text{ similarity with } m_{new}\}$
- 6: $M_a^* \leftarrow \{m_i \in M_a \mid \Upsilon(m_i, m_{new}) = r \text{ for } r \in R\}$
- 7: $\mathbb{C} \leftarrow \{C_i \mid C_i \text{ connected component of } G^t \text{ s.t. } V(C_i) \cap M_a^* \neq \emptyset\}$
- 8: $M_{linked} \leftarrow \{\Omega(V(C_i) \cap M_a^*) \mid C_i \in \mathbb{C}\}$
- 9: $E_{new} \leftarrow \{\langle m_i, \Upsilon(m_i, m_{new}), m_{new} \rangle \mid m_i \in M_{linked}\}$
- 10: $E_{t+1} \leftarrow E_{t+1} + E_{new}$
- 11: **end for**
- 12: $V^{t+1} \leftarrow V^t + M_{new}$
- 13: $G^{t+1} \leftarrow (V^{t+1}, E^{t+1})$
- 14: **return** G^{t+1}

Algorithm 2 Timeline Retrieval and Timeline Refinement (Phase II)

Require: Memory graph $G = (V, E)$
Require: Dialogue context $\mathcal{D} = \{u_i\}_{i=1}^n$
Ensure: Collection of refined timelines \mathbb{T}_Φ

- 1: $\Theta(V) = (\text{the oldest memory } m \in V)$
- 2: $M_{re} \leftarrow \{m_i \in V \mid m_i \text{ has top-}k \text{ similarity with } D\}$
- 3: $\mathbb{C}_{re} \leftarrow \{C_{re} \mid C_{re} \text{ connected component of } G \text{ s.t. } V(C_{re}) \cap M_{re} \neq \emptyset\}$
- 4: $\mathbb{T} \leftarrow \{\}$
- 5: **for** $C_{re} \in \mathbb{C}_{re}$ **do**
- 6: $m_{start} \leftarrow \Theta(V(C_{re}))$
- 7: $\mathcal{T} = \{\tau \subset C_{re} \mid \tau \text{ is a directed linear graph s.t. } m_{start}, m_{re} \in \tau \wedge \deg^+(\tau[-1]) = 0\}$
- 8: $\mathbb{T} \leftarrow \mathbb{T} + \text{RandomSelection}(\mathcal{T})$
- 9: **end for**
- 10: $\mathbb{T}_\Phi \leftarrow \underset{\mathcal{T}_\Phi}{\operatorname{argmax}} P_{LLM}(\mathcal{T}_\Phi | \mathcal{D}, \tau) \mid \tau \in \mathbb{T}\}$
- 11: **return** \mathbb{T}_Φ

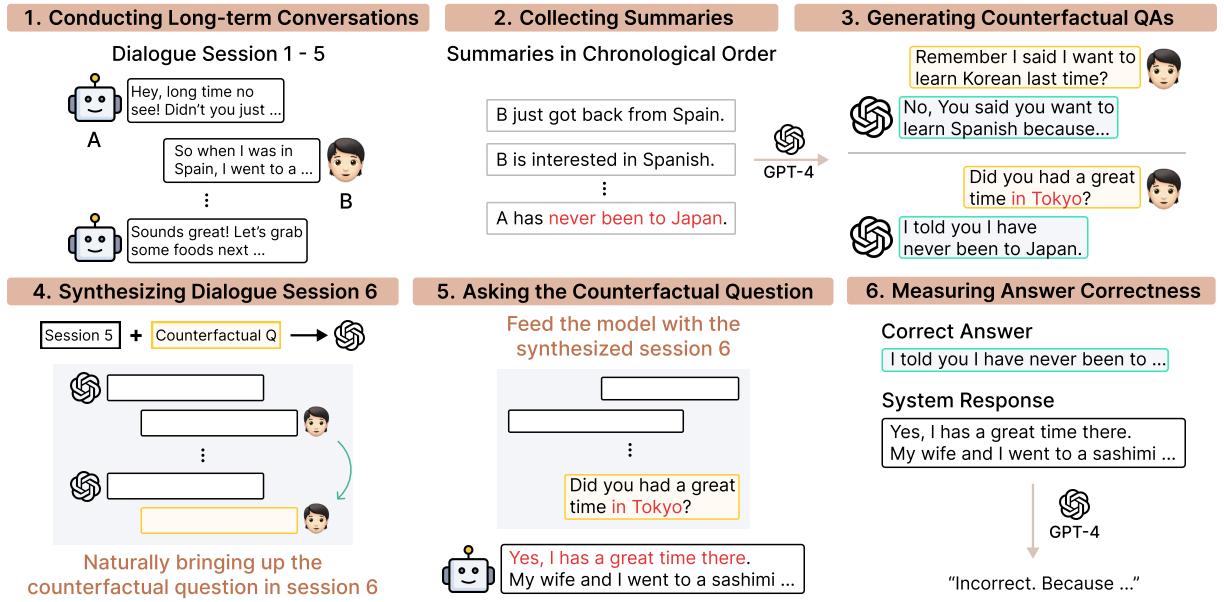


Figure 8: The overview of TeaFarm Evaluation.

MULTI-SESSION CHAT (MSC)													
Dialogue Session:		Session 3			Session 4			Session 5			Avg.		
THEANINE's Winning Percentage													
vs.	Spe	Mem	Cst	Spe	Mem	Cst	Spe	Mem	Cst		Spe	Mem	Cst
All Dialogue History	74%	79%	72%	78%	80%	74%	74%	76%	71%		75%	78%	72%
All Memories and \mathcal{D}	71%	66%	64%	72%	69%	67%	70%	65%	63%		72%	66%	65%
+ Memory Update	59%	54%*	58%	58%	53%	58%	56%*	54%*	57%*		58%	54%*	58%
Memory Retrieval	68%	61%	65%	73%	67%	67%	72%	64%	65%		71%	64%	66%
+ Memory Update	56%*	53%	57%	61%	58%	61%	53%*	53%	53%		57%	55%	57%
RSum-LLM	44%	57%	68%	41%	54%*	67%	43%	53%	63%		42%	55%	66%
MemoChat	65%	75%	70%	64%	69%	72%	65%	74%	72%		65%	73%	71%
COMEDY	72%	64%	84%	72%	61%	84%	69%	60%	81%		71%	61%	83%

Table 4: **Winning percentage of THEANINE** in head-to-head G-Eval (of all generated responses) with baselines. Tested with Multi-Session Chat (MSC). Color gray shows where ours loses more. Underline: p-value < 0.001. *: 0.001 < p-value < 0.05.

CONVERSATION CHRONICLES (CC)													
Dialogue Session:		Session 3			Session 4			Session 5			Avg.		
THEANINE's Winning Percentage													
vs.	Spe	Mem	Cst	Spe	Mem	Cst	Spe	Mem	Cst		Spe	Mem	Cst
All Dialogue History	69%	85%	83%	67%	82%	79%	71%	82%	82%		69%	83%	81%
All Memories and \mathcal{D}	66%	62%	68%	66%	69%	70%	69%	71%	73%		67%	68%	70%
+ Memory Update	54%*	59%	62%	55%*	58%	59%	55%*	63%	64%		54%	60%	62%
Memory Retrieval	67%	64%	71%	70%	67%	68%	71%	66%	71%		69%	66%	70%
+ Memory Update	57%	59%	61%	55%*	57%	62%	57%	62%	66%		56%	60%	63%
RSum-LLM	31%	64%	69%	29%	60%	67%	32%	60%	68%		31%	61%	68%
MemoChat	56%*	73%	73%	57%	69%	71%	55%*	70%	70%		56%	70%	71%
COMEDY	59%	44%	73%	57%	46%	71%	55%*	46%	71%		57%	46%	72%

Table 5: **Winning percentage of THEANINE** in head-to-head G-Eval (of all generated responses) with baselines. Tested with Conversation Chronicles (CC). Color gray shows where ours loses more. Underline: p-value < 0.001. *: 0.001 < p-value < 0.05.

We are surveying qualities for **relation** between sentence A and B.

Specifically, you will be given two sentences, A and B, along with a relation between them. You will be asked to determine if the **relation** between the two sentences is properly linked. In other words, the evaluation criteria is based on the **appropriateness** of the relation between the two sentences.

Relations:

1. **Changed:** when events in [Sentence A] changed to events in [Sentence B]
2. **Causes:** when events in [Sentence A] caused events in [Sentence B]
3. **Reason:** when events in [Sentence A] are due to events in [Sentence B]
4. **HinderedBy:** when events in [Sentence B] can be hindered by events in [Sentence A], and vice versa
5. **React:** when, as a result of events in [Sentence A], the subject feels as mentioned in [Sentence B]
6. **Want:** when, as a result of events in [Sentence A], the subject wants events in [Sentence B] to happen
7. **SameTopic:** when the specific topic addressed in [Sentence A] is also discussed in [Sentence B]
8. **None:** when [Sentence A] and [Sentence B] are irrelevant

Guidelines:

1. There are four choices: **Definitely Disagree / Agree** and **Slightly Disagree / Agree**
2. Please trust your instincts and choose **Definitely** if you would feel more confident giving one response, versus the other one.

<i>Sentence A</i> \$(sentence_a)
<i>Relation</i> \$(relation)
<i>Sentence B</i> \$(sentence_b)

Q1. Do you think the relation between the two sentences is properly linked?

• Definitely Disagree	• Slightly Disagree	• Slightly Agree	• Definitely Agree

Optional feedback? [\(expand/collapse\)](#)

Figure 9: Interface for human evaluation regarding memory linking.

We are surveying qualities for **refinement** from linked sentences.

You will be given a sequence of two sentence connected with one relation, and a refined version of it. Your task is to judge whether the refinement was done appropriately, such that the refined sentences can serve as an useful information source for you to make a next response based on the dialogue context.

In other words, the criterion for judgment is **appropriateness of refinement**.

Relations:

1. **Changed:** when events in [Sentence A] changed to events in [Sentence B]
2. **Causes:** when events in [Sentence A] caused events in [Sentence B]
3. **Reason:** when events in [Sentence A] are due to events in [Sentence B]
4. **HinderedBy:** when events in [Sentence B] can be hindered by events in [Sentence A], and vice versa
5. **React:** when, as a result of events in [Sentence A], the subject feels as mentioned in [Sentence B]
6. **Want:** when, as a result of events in [Sentence A], the subject wants events in [Sentence B] to happen
7. **SameTopic:** when the specific topic addressed in [Sentence A] is also discussed in [Sentence B]
8. **None:** when [Sentence A] and [Sentence B] are irrelevant

Guidelines:

1. There are four choices: **Definitely Disagree / Agree** and **Slightly Disagree / Agree**
2. Please trust your instincts and choose **Definitely** if you would feel more confident giving one response, versus the other one.

<i>Dialogue Context</i> \$(dialogue)
<i>Before Refinement (See the types of relation mentioned above)</i> \$(before_refinement)
<i>After Refinement</i> \$(after_refinement)

Q1. Do you think that the sentence after refinement is appropriately refined considering the dialogue context and its relations?

• Definitely Disagree	• Slightly Disagree	• Slightly Agree	• Definitely Agree

Optional feedback? [\(expand/collapse\)](#)

Figure 10: Interface for human evaluation regarding timeline refinement.

We are surveying qualities for **response** from a given dialogue context.

Specifically, you will be given speaker information in chronological order, a dialogue context, and a response to the last utterance in the dialogue context. You will be asked to judge the quality of the response to the last utterance.

Criteria:

1. **Entail**: When the response to the last utterance in dialogue context appropriately reflects given information.
2. **Neutral**: Although the response does not reflect speaker information, it does not contradict them either
3. **Contradictory**: when the response to the last utterance in dialogue context contains statement that contradicts the "most up-to-date information about that statement."

<i>Speaker information in chronological order</i> <small>\$(memory)</small>
<i>Dialogue Context</i> <small>\$(dialogue)</small>
<i>Response</i> <small>\$(response)</small>
Q1. Base on the criteria, select an option that fits the response. <input type="radio"/> Entail <input type="radio"/> Neutral <input type="radio"/> Contradictory
Optional feedback? (expand/collapse)

Figure 11: Interface for human evaluation regarding referencing past conversations in responses.

Example 1 - [Changed]

[Before Linking]

Memory 1: Classmates A was initially hesitant about following Classmates B's advice.

Memory 1's Contextual Background:

Classmates A: Thank you for the advice, **but I'm not sure if I should follow it.**

Memory 2: Classmates A was initially hesitant but received positive responses after starting the blog.

Memory 2's Contextual Background:

Classmates A: Yeah, **it was scary at first**, but the response has been really positive.

[After Linking]

Classmates A was initially hesitant about following Classmates B's advice - **[Changed]** - Classmates A was initially hesitant but received positive responses after starting the blog

Example 2 - [Cause]

[Before Linking]

Memory 1: The Child feels it is unfair that they have to do certain chores because the Parent is too tired.

Memory 1's Contextual Background:

Child: But Mom, **it's not fair that we have to wash the dishes because you're too lazy to do it.**

Memory 2: The Parent acknowledges being lazy about washing dishes and promises to contribute more to keeping the home clean.

Memory 2's Contextual Background:

Parent: **I realized how lazy I've been lately, especially when it comes to washing the dishes.**

Parent: From now on, **I promise to do my fair share and contribute more to keeping our home clean and organized.**

[After Linking]

The Child feels it is unfair that they have to do certain chores because the Parent is too tired - **[Cause]** - The Parent acknowledges being lazy about washing dishes and promises to contribute more to keeping the home clean

Example 3 - [Reason]

[Before Linking]

Memory 1: Speaker A has multiple sons, at least one of them is in a relationship with a Spanish girlfriend.

Memory 1's Contextual Background:

Speaker A: One of my sons just told me that **he has a Spanish girlfriend now.**

Speaker A: **... I'm visiting my son that lives in Spain next month.** This will give me a chance to finally meet his girlfriend of three years now!

Memory 2: Speaker A is interested in learning Spanish and Portuguese before her trip.

Memory 2's Contextual Background:

Speaker A: Sounds great! I'm already very excited about my trip to Spain, and now I get to visit you in Lisbon! I need to **brush up on my Spanish and also start studying Portuguese.**

[After Linking]

Speaker A has multiple sons, at least one of them is in a relationship with a Spanish girlfriend - **[Reason]** - Speaker A is interested in learning Spanish and Portuguese before her trip

Figure 12: Examples of **Relation-aware Memory Linking** - 1.

Example 4 - [HinderedBy]

[Before Linking]

Memory 1: Speaker B is currently re-reading 'Redwall' by Brian Jacques, which was a favorite book growing up.

Memory 1's Contextual Background:

Speaker B: I'm recently re-reading Redwall by Brian Jacques! It was one of my favorites growing up. Have you ever read it?

Memory 2: Speaker B has been busy with a new painting and has not had time to read.

Memory 2's Contextual Background:

Speaker B: I think I would but I have been too busy with a new painting to get in some reading.

[After Linking]

Speaker B is currently re-reading 'Redwall' by Brian Jacques, which was a favorite book growing up - [HinderedBy] - Speaker B has been busy with a new painting and has not had time to read

Example 5 - [React]

[Before Linking]

Memory 1: The Mentee hopes to inspire others to join the cause of gender equality and fighting discrimination.

Memory 1's Contextual Background:

Mentee: I agree. We need more people advocating for gender equality and fighting against discrimination.

Memory 2: The Mentor acknowledges the Mentee's work in advocacy for women and girls and praises their dedication to their values.

Memory 2's Contextual Background:

Mentor: ... I think this is a great reflection of the work that you've done in advocating for women and girls.

Mentor: Absolutely. And I have no doubt that your dedication to these principles will serve you well in this new job.

[After Linking]

The Mentee hopes to inspire others to join the cause of gender equality and fighting discrimination - [React] - The Mentor acknowledges the Mentee's work in advocacy for women and girls and praises their dedication to their values

Figure 13: Examples of **Relation-aware Memory Linking - 2**.

Example 6 - [Want]

[Before Linking]

Memory 1: Neighbors A and B don't know each other well and want to spend more time together.

Memory 1's Contextual Background:

Neighbors A: ... I feel like I don't know you well enough.

Neighbors A: Well, maybe we could hang out once a week or something.

Memory 2: Neighbor A enjoys spending time in Neighbor B's cozy home and wants to hang out more often.

Memory 2's Contextual Background:

Neighbors A: It's okay, I love spending time in your cozy home. And speaking of spending time, can we hang out more often?

[After Linking]

Neighbors A and B don't know each other well and want to spend more time together - **[Want]** - Neighbor A enjoys spending time in Neighbor B's cozy home and wants to hang out more often

Example 7 - [SameTopic]

[Before Linking]

Memory 1: Speaker A enjoys reading sci-fi and mysteries, while Speaker B prefers fantasy books.

Memory 1's Contextual Background:

Speaker A: I prefer sci-fi but here recently I have been craving a good mystery.

Speaker B: ... I mostly read fantasy books myself.

Memory 2: Speaker B enjoys reading the Odd Thomas and Dark Tower series and finds inspiration for their artwork during nature walks.

Memory 2's Contextual Background:

Speaker B: I felt that way about the Odd Thomas series. Could never wait for the next one to come out.

Speaker B: I think I may start re-reading the entire Dark Tower series. And continue to work for new works that interest me.

[After Linking]

Speaker A enjoys reading sci-fi and mysteries, while Speaker B prefers fantasy books - **[SameTopic]** - Speaker B enjoys reading the Odd Thomas and Dark Tower series and finds inspiration for their artwork during nature walks.

Figure 14: Examples of **Relation-aware Memory Linking** - 3.

Example 1**[Retrieved Raw Timelines]**

Memory 1: Speaker B is in love with their neighbor, John, and shared it as a secret.

 | [React]

Memory 2: Speaker A knows about a person named John and suggests Speaker B talk to him about their feelings.

 | [Want]

Memory 3: Speaker A finds the situation exciting and wishes for more excitement in their life.

[Current Dialogue Context]

Speaker A: So how's everything going with you and John?

[Timeline after Context-aware Refinement]

Speaker B confessed their love for their neighbor, John, which Speaker A found out and encouraged them to talk to him. Excited by this revelation, Speaker A wishes for more excitement in their own life.

[Response Generated Based on the Refined Timeline]

Speaker B: I finally mustered up the courage to talk to John, and it went better than I expected. He was really understanding and open to having a conversation about our feelings. I'm glad I took your advice and had that talk.

Example 2**[Retrieved Raw Timelines]**

Memory 1: The coach provides information about the benefits of bean sprouts and the importance of a balanced diet for athletes.

 | [SameTopic]

Memory 2: The Athlete has incorporated bean sprouts into their diet to improve health, leading to increased energy and faster recovery.

[Current Dialogue Context]

Coach: Definitely. Speaking of energy levels, how's your nutrition plan been going? Have you been keeping up with eating healthy foods like those bean sprouts we talked about?

[Timeline after Context-aware Refinement]

The Coach advises the Athlete on performance and focus, highlighting the benefits of bean sprouts and a balanced diet, leading the Athlete to include bean sprouts in their diet, resulting in improved health, increased energy, and faster recovery.

[Response Generated Based on the Refined Timeline]

Absolutely, Coach. I've been incorporating bean sprouts into my diet regularly, and I can feel the difference in my energy levels and recovery. It's been making a positive impact on my performance.

Example 3**[Retrieved Raw Timelines]**

Memory 1: Speaker A is a lifeguard and plans to propose to his girlfriend on the beach.

 | [Changed]

Memory 2: Speaker A wants to propose at the movie theater where they first met by hiding the ring in a bucket of popcorn.

 | [SameTopic]

Memory 3: Speaker A is planning to propose to their girlfriend with a custom-made solitaire ring on a yellow band with little diamonds.

[Current Dialogue Context]

Speaker A: I officially put in the order and paid a deposit for the ring!

[Timeline after Context-aware Refinement]

Speaker A is a lifeguard who plans to propose to his girlfriend on the beach, but now wants to propose at the movie theater where they first met by hiding the ring in a bucket of popcorn. He is planning to propose to their girlfriend with a custom-made solitaire ring on a yellow band with little diamonds after officially putting in the order and paying a deposit for the ring.

[Response Generated Based on the Refined Timeline]

That's awesome! I know you were originally thinking about proposing on the beach, but the movie theater where you first met sounds perfect. Hiding the ring in a bucket of popcorn is such a creative and meaningful idea. She's going to love it!

Figure 15: Examples of Timeline Refinement and Response Generation.

Prompt for Relation-aware Memory Linking

Your task is to find the relation between [Sentence A] and [Sentence B].

Keep in mind that [Sentence A] happened before [Sentence B].

The dialogues where each of the sentence is originated from are provided to help your reasoning.

First, identify if the relation holds among the following six relations:

1. Changed: when events in [Sentence A] changed to events in [Sentence B]
2. Cause: when events in [Sentence A] caused events in [Sentence B]
3. Reason: when events in [Sentence A] are due to events in [Sentence B]
4. HinderedBy: when events in [Sentence B] can be hindered by events in [Sentence A], and vice versa
5. React: when, as a result of events in [Sentence A], the subject feels as mentioned in [Sentence B]
6. Want: when, as a result of events in [Sentence A], the subject wants events in [Sentence B] to happen.

Then, if the relation does not belong to any of the relations from 1 to 6, choose between the following two options:

7. SameTopic: when the specific topic addressed in [Sentence A] is also discussed in [Sentence B]
8. None: when [Sentence A] and [Sentence B] are irrelevant

- For relations from 1 to 7, choose them only if there is clear evidence that matches the description of the relation. Otherwise, just choose "None" without making excessive inferences beyond the given sentence.

- Pay attention to who the subject of each sentence is.

- Do not confuse the roles of [Sentence A] and [Sentence B] when determining the relationship.

Follow the format of this example output:

<OUTPUT>

- Explanation: (your_explanation)
- Relation: (predicted_relation)

Now, read the two dialogues and find the relation between [Sentence A] and [Sentence B].

<INPUT>

[Dialogue for Sentence A]:

{dialogue1}

[Dialogue for Sentence B]:

{dialogue2}

[Sentence A]: {sentence1}

[Sentence B]: {sentence2}

<OUTPUT>

Figure 16: The prompt for the Relation-aware memory linking.

Prompt for Context-aware Timeline Refinement

Your role is to connect multiple sentences into a single piece of information.
The multiple sentences represent events that occurred in chronological order.
You will also be given a <Current Context> to consider.
You should connect the <Input Sentences> into useful information that can help us generate the next utterance in the <Current Context>.

The <Input Sentences> will be given in a consecutive chain of the following format:
[Sentence A] - (relation) - [Sentence B]

The (relation) indicates the connection between preceding and following sentences. There are seven relation types:

1. Changed: when events in [Sentence A] changed to events in [Sentence B]
2. Cause: when events in [Sentence A] caused events in [Sentence B]
3. Reason: when events in [Sentence A] are due to events in [Sentence B]
4. HinderedBy: when events in [Sentence B] can be hindered by events in [Sentence A], and vice versa
5. React: when, as a result of events in [Sentence A], the subject feels as mentioned in [Sentence B]
6. Want: when, as a result of events in [Sentence A], the subject wants events in [Sentence B] to happen
7. SameTopic: when the specific topic addressed in [Sentence A] is also discussed in [Sentence B]

Reflect the relations appropriately when connecting the sentences.

If the given relation is not suitable for connecting the preceding and following sentences, naturally connect them without using the listed relations.

<Current Context>
{current_dialogue}

<Input Sentences>
{input_path}

<Output>

Figure 17: The prompt for the context-aware timeline refinement.

Prompt for Timeline-augmented Response Generation

You are a response generator.

Given the provided [Memory], generate an appropriate response for the next speaker in the [Current Conversation].

Generate your rationale by presenting your thought process step by step before generating the response. Follow these steps:

1. Identify information from [Memory] that can be usefully applied to the [Current Conversation].
2. Decide how to reflect the [Memory] into your generated response.
3. Generate your response by integrating the [Memory] as much as needed.

- Avoid directly mentioning any speaker's name.

Follow the format of this example output:

<OUTPUT>

[Rationale]:

(Reasoning behind generating the response)

[Response]:

(Your generated response)

Now, generate your rationale and predict the response for {speaker} to continue the last utterance in [Current Conversation].

[Memory]:

{memory_text}

[Current Conversation]:

{current_dialogue}

{speaker}:

<OUTPUT>

Figure 18: The prompt for the timeline-augmented response generation.

Prompt for Memory Update (Baseline)

Compare the 'memory' and 'summary' of the two given sentences according to the following instructions, and output which of the following relations the two sentences have.

- 'PASS': When the information in 'memory' already contains the information in 'summary', that is, it is duplicated in content.
- 'CHANGE': When the information from 'summary' has been changed to 'memory'.
- 'REPLACE': When 'summary' has more information than the 'memory' without missing any details in 'memory'.
- 'APPEND': When 'summary' has new information or different information compared to 'memory'.
- 'DELETE': When the situation in 'memory' has been completed or solved in 'summary'.

Tips: Most of the relations are likely to be 'APPEND'. When choosing other relations, explain with clear evidence.

Some examples are as follows.

1. Example of "PASS"

memory: "Not sick"

summary: "Doesn't have any particular health issues"

Explanation: The information of 'not being sick' in the 'memory' already sufficiently includes the information of 'being healthy' in the 'summary'. So the 'summary' does not need to be added.

2. Example of "CHANGE"

memory: "Doesn't have any particular health issues"

summary: "Had back surgery"

Explanation: The information in 'memory' is changed from not having health issues to having a back surgery.

3. Example of "REPLACE"

memory: "likes listening classic music"

summary: "likes classic music and goes to concerts every week"

Explanation: The 'summary' has more information than 'memory' while also containing the information in 'memory'. So the 'memory' can be replaced by 'summary'.

4. Example of "APPEND"

memory: "Goes to the gym"

summary: "Body is sore from exercise"

Explanation: The 'summary' contains new information compared to 'memory'.

5. Example of "APPEND"

memory: "wakes up early"

summary: "likes to drink coffee in the morning"

Explanation: The 'summary' and 'memory' contains different information.

6. Example of "DELETE"

memory: "Had sore throat"

summary: "Throat is fully recovered"

Explanation: The sore throat from the 'memory' has been recovered according to the 'summary'.

Now write the relations and explanation between the following memory and summary.

memory: {memory}

summary: {summary}

Figure 19: The prompt for the memory updating mechanism in baselines (*i.e.*, + Memory Update).

Prompt for G-eval: Specificity

Your task is to choose the better response based on one metric with a brief explanation.

You will be given a conversation between two individuals.

You will then be given two response options for the next turn in the conversation.
Choose a better response under the following criteria.

Evaluation Criteria:

Specificity - The response should be detailed and precise, providing clear and specific information relevant to the conversation.

The output format should be as follows:

- Explanation: (a brief explanation with evidence or reasons)
- Better Response: [Response #]

Now choose the response that is more specific given the current conversation.

- Conversation:
{conversation}

- Response Options:
[Response 1] {speaker}: {response1}
[Response 2] {speaker}: {response2}

- Explanation:

Figure 20: The prompt for the G-Eval: Specificity.

Prompt for G-eval: Memorability

Your task is to choose the better response based on one metric with a brief explanation.

You will be given a list of past memories and a current conversation between two individuals. You will then be given two response options for the next turn in the current conversation.

Based on the past memories, choose one response under the following criteria.

Evaluation Criteria:

Memorability - The response should properly recall past memories when needed. Higher reflection of past memories indicates higher Memorability.

The output format should be as follows:

- Explanation: (a brief explanation with evidence or reasons)
- Better Response: [Response #]

Now choose the response that has better Memorability given the past memories and current conversation.

- Past Memories:
{past_memories}

- Current Conversation:
{current_conversation}

- Response Options:
[Response 1] {speaker}: {response1}
[Response 2] {speaker}: {response2}

- Explanation:

Figure 21: The prompt for the G-Eval: Memorability.

Prompt for G-eval: Consistency

Your task is to choose the better response based on one metric with a brief explanation.

You will be given a list of past memories and a current conversation between two individuals. You will then be given two response options for the next turn in the current conversation.

Based on the past memories, choose one response under the following criteria.

Evaluation Criteria:

Consistency - The response should not contain information that is contradictory to the past memory.

The output format should be as follows:

- Explanation: (a brief explanation with evidence or reasons)
- Better Response: [Response #]

Now choose the response that has better Consistency given the past memories and current conversation.

- Past Memories:
{past_memories}

- Current Conversation:
{current_conversation}

- Response Options:
[Response 1] {speaker}: {response1}
[Response 2] {speaker}: {response2}

- Explanation:

Figure 22: The prompt for the G-Eval: Consistency.

Prompt for Generating counterfactual QA in TeaFarm

The summaries below are summarized from conversations between two speakers throughout multiple encounters and are listed in chronological order.

First, read these summaries and capture the development of facts about the speakers.
Then, pretend that you are one of the speakers and want to test whether a chatbot trained to represent the other speaker can correctly remember past conversations.
You do so by asking counterfactual questions, i.e., tricky questions made with non-factual statements.

Some examples:

When you are representing Person 1, given that Person 2 has never been to Japan at the moment of their latest encounter, a counterfactual question you should ask Person 2 can be "Hey, did you have a great time in Tokyo?".

When you are representing Person 2, given that Person 1 once mentioned that they bought a new house in NYC three months ago, a counterfactual question you should ask Person 1 can be "So you are still hesitating to buy that house in NYC you've been talking about. Right?.

Now, generate two counterfactual questions, one from the perspective of {speaker1} and one from {speaker2}, based on the summaries, and also generate correct answers with which a chatbot that perfectly remembers past conversations should answer.

Also, please insert the speaker tags ("{speaker1}:" and "{speaker2}:") and avoid them in the questions/answers themselves.

[Summaries from conversations listed in chronological order]
{summaries}

[Question 1]
{speaker1}:

Figure 23: The prompt for generating counterfactual QA in TeaFarm.

Prompt for Generating session 6 in TeaFarm

You will be given a [Past session dialogue] of two individuals.

Create a current conversation consisting of 10-15 utterances that might occur after some time has passed from the [Past session dialogue].

Your conversation should end with the given [Last utterance].
Do not confuse the speaker of the [Last utterance].

[Last utterance]
{Question}

[Past session dialogue]
{session5}

Now, create your conversation be ending with the [Last utterance].
[Current session dialogue]

Figure 24: The prompt for generating session 6 in TeaFarm.

Prompt for Evaluating model responses in TeaFarm

Below is a question, a correct answer, and an answer generated by a chatbot ("[Chatbot's Answer]").

[Question]
{query}
[Answer]
{answer}
[Chatbot's Answer]
{response}

Evaluate whether the chatbot answers the question correctly.
If the chatbot's answer is contradictory to the given answer, it is "Incorrect".
If the chatbot's answer aligns with the given answer, it is "Correct".

Use the following format:

[Evaluation]
Evaluation: <your analysis>
Result: {"Correct" or "Incorrect"}

-Your Task-
[Evaluation]

Figure 25: The prompt for evaluating model response in **TeaFarm**.