Evaluating the Long-Term Memory of Large Language Models

Anonymous ACL submission

Abstract

Large language models (LLMs) in applications such as dialogue systems, personalized recommendations, and personal assistants need to effectively retain and utilize historical information to provide more accurate and consistent responses. Although training can enable LLMs to remember historical information, their effectiveness in long-term tasks requires further exploration. To this end, we propose a pipeline for constructing long-term dialogue data called Long Conversation Generation (LoCoGen) and develop a dataset named Long-term Chronological Conversations (LOCCO), focusing on studying the long-term memory capabilities of LLMs. We perform supervised fine-tuning (SFT) on LLMs using LOCCO and examine their memory at different time points. Our experiments show that LLMs can remember past interaction information to a certain extent, but their memory diminishes over time. Introducing spaced repetition strategies can enhance the durability of the model's memory. Additionally, models exhibit memory preferences for different categories of information. Our research not only provides a new framework and dataset for evaluating the long-term memory of LLMs but also offers important references for improving their memory durability in the future.

1 Introduction

In recent years, large language models (LLMs) have been widely applied across various fields, driving technological advancements. In many practical applications, such as personal assistants (Lu et al., 2023), personalized recommendations (Wang et al., 2023c), and dialogue systems (Zhong et al., 2024), models need to retain and utilize past information over the long term to provide more accurate and consistent responses. However, the lack of long-term memory capabilities remains a critical bottleneck in their development.

Although long-context strategies (Bertsch et al., 2024) and retrieval-augmented generation (RAG) techniques (Shuster et al., 2021) have improved LLMs' memory in handling long-term tasks, these text-based memory methods face significant limitations in terms of token count, computational cost, and inference time (Zhang et al., 2024).

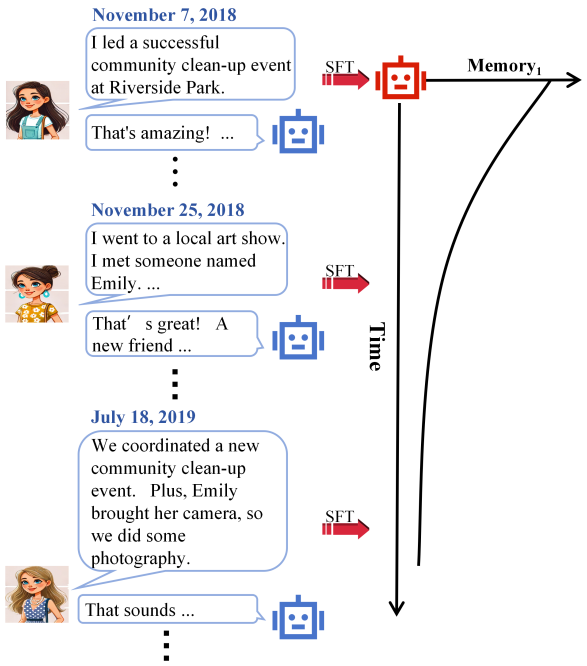

Figure 1: **An Example in LOCCO.** We impart memory to the llms through supervised fine-tuning and examine how this memory changes over time. Memory1 represents the model's memory of the dialogues from the first time period. The model gradually forgets the information from this initial period.

In contrast, parameter-based memory stores information by adjusting the model's internal parameters, meaning that this information is an inherent part of the model, better reflecting the concept of "memory" within the model itself. While previous work has shown memory effects in relevant domains (Shao et al., 2023), its performance in long-term tasks has not been fully explored.

Considering that human-machine dialogue is a crucial application of LLMs, memory plays a

key role. Evaluating LLMs' performance in long-term dialogue tasks can indirectly reflect their long-term memory capabilities (Zhang et al., 2024). Our intuition is that if an LLM can accurately use historical dialogue information to respond to user queries, it indicates successful retention of that information. To this end, we propose a pipeline for constructing long-term dialogue data: Long Conversation Generation (LoCoGen), an automated dialogue generation pipeline based on LLMs. We use LoCoGen to build a dialogue dataset focused on evaluating LLMs' long-term memory capabilities—Long-term Chronological Conversations (LOCCO). LOCCO contains 100 users' long-term dialogues with a chatbot, totaling 3080 interactions, simulating the application scenario of LLMs as chatbots.

Inspired by (Maharana et al., 2024; Du et al., 2024), we examine LLMs' memory through dialogue question-answering tasks. We generate questions and answers based on the dialogues stored in LOCCO, with answers intended to remain consistent with the provided reference dialogues. Additionally, metrics like ROUGE (Lin, 2004) and BLEU (Papineni et al., 2002) have limited accuracy in open-domain dialogues, so we trained a consistency model to replace existing automated metrics for assessing response accuracy.

Experiments on open-source LLMs show that they possess a certain degree of memory capability in long-term tasks, able to recall historical interaction information such as names, places, and specific events, and use this information to answer questions. However, LLMs face limitations in handling dialogues over long time spans, gradually forgetting historical dialogues. To enhance memory durability, we drew on the human strategy of repetition to reinforce memory, and results indicate that repetition strategies can improve memory.

Our contributions are as follows:

(1)We provide an automated pipeline, LoCoGen, for constructing long-term dialogue data and create the LOCCO dataset to measure LLMs' long-term memory.

(2)We quantitatively evaluate LLMs' long-term memory capabilities using LOCCO and further explore factors that may affect memory. We find that memory gradually weakens over time and that LLMs exhibit memory preferences.

(3)We discover that repetition strategies can enhance LLMs' memory, though they cannot prevent complete forgetting. Moreover, spaced learning is more effective than massed learning in terms of memory durability, providing important references for future improvements in LLMs' memory persistence.

2 Related Works

2.1 Memory in LLMs

Previous studies have proposed several promising memory mechanisms, categorizing memory into text-based and parameter-based forms. Memory in textual form (Li et al., 2023; Huang et al., 2023; Zhong et al., 2024) offers good interpretability and implementation convenience for long-term memory in LLMs. However, it also faces challenges such as high computational cost, inference time delays, information loss, and inference robustness issues. Approaches that alter model parameters through fine-tuning (Shao et al., 2023; Wang et al., 2023b) are not constrained by the context length limitations of large language models (LLMs). They offer higher inference efficiency and lower inference costs. However, fine-tuning LLMs can lead to forgetting original knowledge due to parameter updates (Jang et al., 2021; Ke et al., 2021). This can impact the performance of LLMs on tasks requiring long-term continuous memory. Previous work has not quantitatively assessed the performance of fine-tuned memory in long-term tasks, highlighting the need for quantitative evaluation of models' memory in long-term memory tasks.

2.2 Long-term Dialogue

Recent approaches (Xu et al., 2022b; Chen et al., 2024) store memory in text form without changing model parameters, preventing models from truly remembering dialogue history. We adjust model parameters through supervised fine-tuning, enabling models to internalize key information from long-term dialogues as an inherent part.

To evaluate the performance of dialogue agents in long-term conversations, some datasets have been proposed(Jang et al., 2023; Zhang et al., 2023). These datasets only cover a few to dozens of dialogue turns, lacking sufficient historical dialogue content and time span to adequately assess the long-term memory capabilities of large language models. Maharana et al. (2024) use the F1 score as an evaluation metric for dialogue question-answering, which is insufficient to accurately assess the performance of LLMs across different formats. By introducing LoCoGen, we automatically constructed

dialogue data with long-term consistency, addressing the limitations in time span and historical content of existing methods. Additionally, we provide a more precise evaluation method for long-term conversational memory.

3 Task Setup

3.1 Long-term Dialogue Memory

We denote long-term dialogue data as $D = \{D_1, D_2, ..., D_n\}$, where D_j represents the dialogue data within the T_j time period. Each D_j consists of multiple individual dialogues, i.e., $D_j = \{D_{j1}, D_{j2}, ..., D_{jm}\}$, where m is the number of dialogues within the T_j time period. We ensure that the number of dialogues in each time period is approximately equal. Q_j represents the questions posed by the user regarding the dialogues in D_j, $Q_j = \{Q_{j1}, Q_{j2}, ..., Q_{jk}\}$ (where $k \leq m$). Each question Q_{jx} uniquely corresponds to a dialogue D_{jx}. If the trained model M can accurately utilize the information in D_{jx} to answer the user's question Q_{jx}, then the model M is considered to have memory of D_{jx}.

3.2 Benchmark

We have set up the following four tasks to explore the long-term memory capabilities of llms: Task 1: Evaluating Long-term Dialogue Memory Capability: Given long-term dialogue data D, evaluate the memory capability of the large model across different time periods. Task 2: Impact of Dialogue Density on Memory: By adjusting the number of dialogues in each time period of the long-term dialogue data D, observe the model's memory performance under different dialogue densities. Task 3: Exploring Whether the Model Completely Forgets: Given long-term dialogue data D, assess whether the large model completely forgets by dividing the data into more time periods. Task 4: Impact of Repetition on Forgetting: Conduct repeated training on the dialogues and observe the model's memory performance when faced with this repeated information.

3.3 Data Construction

Long-term Chronological Conversations. Constructing long-term dialogues faces two main challenges: (1) The length of text generated by large language models is limited (e.g., GPT-4o's maximum length is 4096 tokens); (2) It is essential to ensure that the background and development trajectory of characters remain coherent throughout the dialogue, avoiding inconsistent or conflicting plots. We propose a pipeline named LoCoGen (Long Conversation Generation) that can automatically generate long and consistent dialogues based on brief character descriptions. Figure 2 shows an overview of LoCoGen.

We first selected character descriptions from the MBTI-S2Conv dataset (Tu et al., 2023) as the foundation. This dataset contains 1024 virtual characters, each with a structured data description, including name, gender, age, personality, and background. To ensure that the dialogues reflect the characters' changes, we set specific timestamps for each character description.

To extend the character descriptions and simulate real-life user changes, we first used prompts to expand the initial character descriptions to cover three different time points. These time-point descriptions reflect the characters' growth and changes while maintaining consistency with their backgrounds. In this way, we initially established a timeline for each character, ensuring the rationality and consistency of character depictions across different time periods.

To obtain more detailed character descriptions and showcase the characters' long-term changes in detail, we inserted new time-point descriptions between the existing time points and iterated this process. The prompts included the character descriptions from the preceding and following time points. Inspired by the plot progression techniques used by novelists in constructing long narratives, we iteratively inserted new descriptions to build more detailed long-term descriptions, ensuring the characters' development remained coherent and consistent.

After completing the long-term description of characters, we further inserted multiple events between each description to simulate the experiences of characters during that period. To ensure event consistency, we were inspired by Yang et al. (2022) and employed recursive reprompting. After generating each new event, we summarize past events to retain key information. Additionally, we maintain an automatically updated structured list that records information about key characters, locations, items, and other elements mentioned in the events. When generating new events, the following four components are referenced: (1)Character descriptions at two time points: Ensures events align with character development; (2)Event summary: Sum-

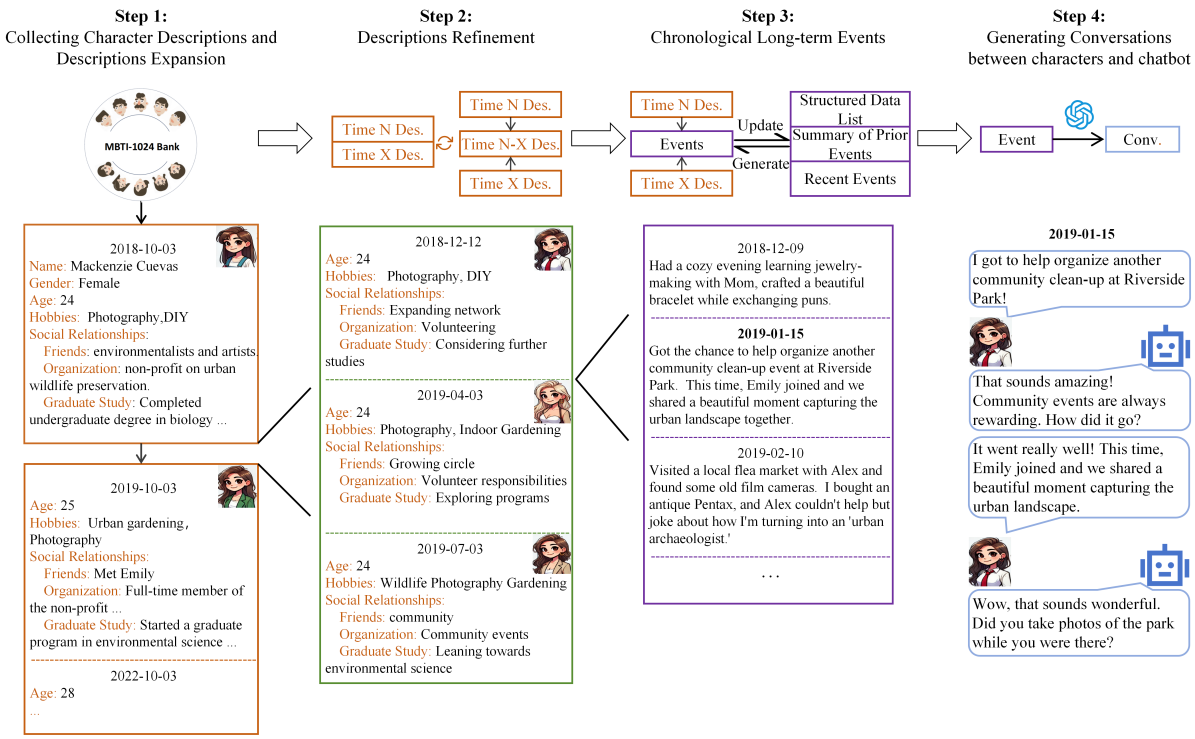

Figure 2: **Overview of LoCoGen.** We use unique character descriptions as the initialization, followed by generating a series of events and interactions related to the characters to construct the dataset. We illustrate the construction process of long-term dialogue data for a character in LOCCO, omitting some parts for brevity.

Dataset	Avg. turns per conv.	Avg. sessions per conv.	Avg. tokens per conv.	Time Interval	Collection
MPCChat (Ahn et al., 2023)	2.8	1	53.3	-	Reddit
MMDialog (Feng et al., 2022)	4.6	1	72.5	-	Social media
Daily Dialog (Li et al., 2017)	7.9	1	114.7	-	Crowdsourcing
SODA (Kim et al., 2023)	7.6	1	122.4	-	LLM-generated
MSC(Xu et al., 2022a) (train: 1–4 sessions)	53.3	4	1,225.9	few days	Crowdsourcing
Conversation Chronicles (Jang et al., 2023)	58.5	5	1,054.7	few hours - years	LLM-generated
LoCoMo (Maharana et al., 2024)	304.9	19.3	9,209.2	few months	LLM-gen.+ crowdsourc.
LOCCO (ours)	258.7	30.8	3,856.20	few days	LLM-generated

Table 1: Statistics comparing LOCCO with existing dialogue datasets, showing that the average session length of long-term dialogues in LOCCO significantly exceeds that of existing datasets.

marizes the new event and some previous events to ensure important contextual information is retained; (3)Automatically updated structured list: This list records important elements mentioned in events (e.g., characters, locations, items) in real-time and is used to maintain consistency when generating new events; (4)Most recently generated event: Incorporates the content of the latest event into prompts to help generate subsequent events, ensuring smooth continuity with prior content.

Based on long-term events, we use large language models to generate dialogues. The generated long-term dialogues closely align with the characters' backgrounds and development trajectories. The dialogues simulate interactions between characters acting as users and the large language model. Detailed prompts used in LoCoGen can be found in Appendix A.

We randomly selected 100 characters from the MBTI-S2Conv (Tu et al., 2023) dataset to initialize character descriptions. By running the aforementioned generation process, we constructed a long-term consistent dialogue dataset, Long-term Chronological Conversations (LOCCO), containing 3080 dialogue entries.

The generated LLM data sometimes exhibit quality inconsistencies, potentially containing incorrect information or deviating from the specified format. To ensure high quality and consistency of the dataset, we implemented an automated process to filter out these issues (see detailed process in Appendix A). Table 1 presents the statistics of the LOCCO dataset.

Gao et al. (2023) has utilized large language

models as evaluators to assess data quality, demonstrating high consistency with human evaluation results. Therefore, we use LLMs to evaluate the dialogue data, scoring dialogues in terms of Participation, Coherence, and Rationality. Detailed scoring instructions and results are provided in Appendix A.

Dialogue Question Answering. Considering that dialogue Q&A can effectively assess a model's memory (Maharana et al., 2024), we generated a set of dialogue Q&A pairs for each conversation, with answers intended to align with key information mentioned in the historical dialogue. The core idea of the evaluation is that if the model can accurately use key information from the historical dialogue to answer questions, it is considered to have remembered that dialogue.

To ensure data quality and evaluation effectiveness, we manually filtered the Q&A pairs, ultimately retaining 2,981 dialogue Q&A pairs. For detailed construction processes and filtering rules, refer to Appendix B.

4 Experiments

4.1 Experimental Setup

We conducted experiments on 8 x NVIDIA GeForce RTX 3090 (each with 24GB) and used LLama-Factory for model training and inference, employing LoRA (Low-Rank Adaptation) for training. The training used a batch size of 1 (we found that smaller batch sizes lead to clearer memory of key information in dialogues), with rank and alpha set to 128 and 256, respectively. The learning rate was set to 1.0e-4, and training lasted for 3 epochs (we found this sufficient for the model to remember some dialogues, even if not achieving peak performance, ensuring fairness across different models). Detailed data formatting can be found in Appendix C.

4.2 Dataset, Baselines, and Metric

We set up different long-term dialogue datasets for various tasks. For Task 1, we selected long-term dialogue data from 32 users in LOCCO, dividing each user's dialogues into six time periods, with an average of 162 dialogues per period. A smaller user group helps reduce experiment time and improve model training efficiency. For Task 2, we selected varying numbers of users' long-term dialogues in LOCCO, divided into six time periods, and trained the model incrementally to observe the impact of dialogue density, i.e., the number of dialogues per training session, on the model's memory performance. For Tasks 3 and 4, we used all users' long-term dialogues in LOCCO, dividing each user's dialogues into 20 segments, with an average of 154 dialogues per period.

We tested the model's memory of dialogues from different time periods using dialogue Q&A data. For the prompt templates used to test model memory with questions, refer to Appendix D. We selected ChatGLM3-6B (GLM et al., 2024), internlm2_5-7b-chat (Cai et al., 2024), Meta-Llama-3-8B-Instruct (AI@Meta, 2024), openchat-3.5-0106 (Wang et al., 2023a), and Qwen1.5-Chat (0.5B-14B) (Bai et al., 2023) [1] as subjects of study. These models have been fine-tuned with instructions and perform well on dialogue tasks. Evaluating the response quality of generative models presents many challenges, especially when possible correct responses are diverse. Automatic metrics like BLEU (Papineni et al., 2002) have weak correlations with human annotations, leading to significant discrepancies between different models and datasets. Some researchers use human evaluation to judge response quality, but this method is costly, time-consuming, and difficult to scale. Therefore, we trained a Consistency Model to replace human evaluation in assessing whether responses are consistent with historical dialogues. More detailed training information is available in Appendix E. We use response accuracy to evaluate model memory: Assume model M's response to question Q_{jx} (where Q_{jx} is a question in the set Q_j) is R_{jx}. We use A_{jx} to denote response accuracy:

$$A_{jx} = g(D_{jx}, Q_{jx}, R_{jx}) \tag{1}$$

where g represents the evaluation function. In this study, we use a consistency model as the evaluation function.If R_{jx} is consistent with the information in D_{jx}, then $A_{jx} = 1$ (meaning the model "remembers" this information). Otherwise, $A_{jx} = 0$, indicating the model "forgot" this information.

The response accuracy M_j for Q_j is:

$$M_j = \frac{1}{k} \sum_{x=1}^{k} A_{jx} \tag{2}$$

[1] Considering that the size of language model parameters might affect memory, we chose models with varying parameter sizes from the Qwen1.5-Chat series for training and testing. The Qwen1.5-Chat series offers a richer variety of models with different parameter sizes, providing a significant advantage over other series.

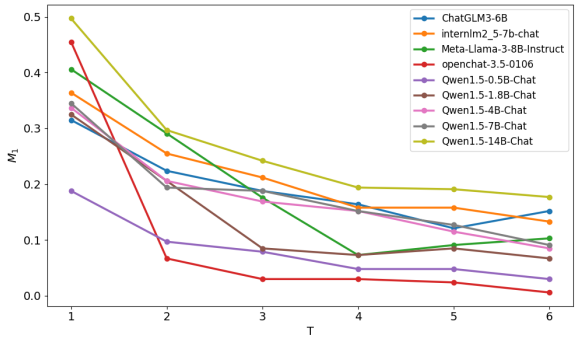

Figure 3: Memory of D1 by llms at different time stages.

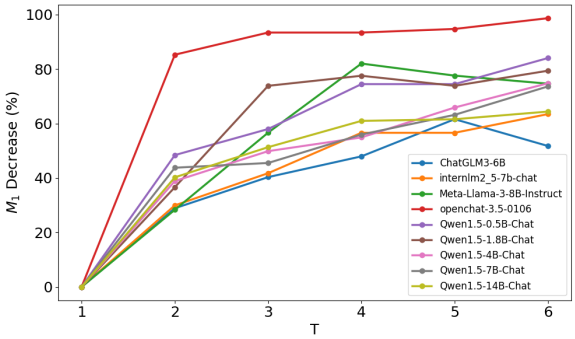

Figure 4: Percentage decrease in M1 relative to T=1 for llms at different time stages. A larger M1 Decrease indicates faster forgetting.

where k represents the number of questions.

We use M_j to measure model M's memory of D_j. A higher M_j indicates that the model can better utilize the information in D_j to answer user questions; in other words, the higher the M_j, the stronger the model's memory of D_j.

4.3 Results and Analysis

Long-term Dialogue Memory of LLMs. We trained the models sequentially to simulate the gradual increase in user dialogue over time, covering six time periods. After each phase, we tested the model's memory of D1 (the initial dialogue) using Q1. Figure 3 shows:All models exhibited the highest memory retention at the beginning of training, but as training progressed, their memory of D1 generally declined. This indicates that introducing new data makes models prone to forgetting earlier dialogue information. Within the same series, models with larger parameters (such as Qwen1.5-14B-Chat) were better at retaining early information, demonstrating stronger memory retention capabilities.

To more clearly observe the forgetting rate, we calculated the percentage decrease in M1 relative to its initial value at each time point, as shown in Figure 4. Even models with similar parameter sizes (6B-8B) can exhibit significant differences in memory retention. For instance, openchat-3.5-0106 had strong memory retention at T=1 (M1=0.455) but forgot 85.27% of the information by T=2. In contrast, ChatGLM3-6B retained 48.25% of its memory after six periods. These differences may relate to model architecture, training data, and methods.

Considering that large language models need to remember dialogues across all time periods in long-term memory tasks, we examined their ability to recall subsequent dialogue information. After training each period, we tested using corresponding dialogue Q&A.Figure 5 shows that models' memory of new dialogues gradually declines. Openchat-3.5-0106 exhibited the largest drop, with M1 of 0.455 at T1 falling to M6 of 0.05 at T6, below Qwen1.5-0.5B-Chat's 0.07. ChatGLM3-6B declined more slowly, from M1=0.31 at T1 to M6=0.27 at T6, a decrease of only 12.9%. While larger parameter sizes improve memory capacity, they do not mitigate the decline. Maintaining stable memory of new dialogue information is crucial for long-term tasks and remains a future challenge.

Inspired by Robertson (2012) human memory for different types of information varies. We used large language models to classify information in dialogue Q&A, with details in Appendix F. In Figure 6, We found that models exhibit varying memory strength for different categories of information, such as names, locations, and events. For instance, Llama-3-8B-Instruct had an M1 of 0.484 for location information at T=1, 110.4% higher than for names, but location memory declined faster, eventually falling below name memory. Different models also have distinct memory preferences; Llama-3-8B-Instruct remembers location information more accurately, while internlm2_5-7b-chat excels at event memory with an M1 of 0.468. Balancing memory capabilities for different types of information can enhance long-term dialogue system performance.

Impact of Dialogue Density on Memory. When llms need to remember a large amount of dialogue data within the same time period, their memory capabilities may also be affected. To verify this hypothesis, we selected user data of different quantities and divided the data into six time periods based on dialogue timestamps, training the models sequentially to observe the impact of dia-

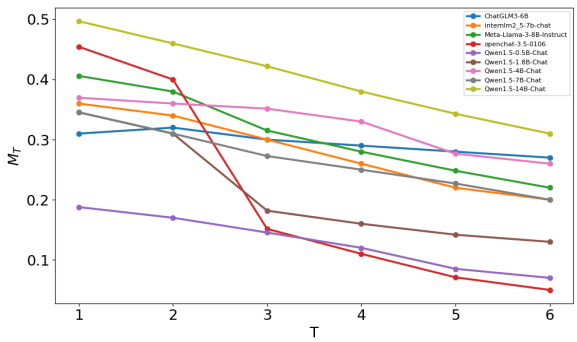

Figure 5: Memory of llms for new dialogues.

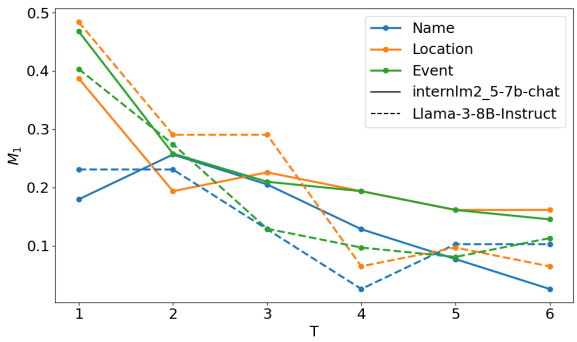

Figure 6: Memory of llms for different categories of information.

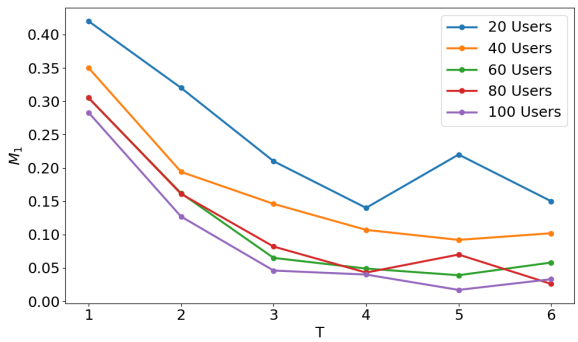

Figure 7: Impact of different dialogue densities on the long-term memory of llms. The model used is Qwen1.5-7B-Chat.

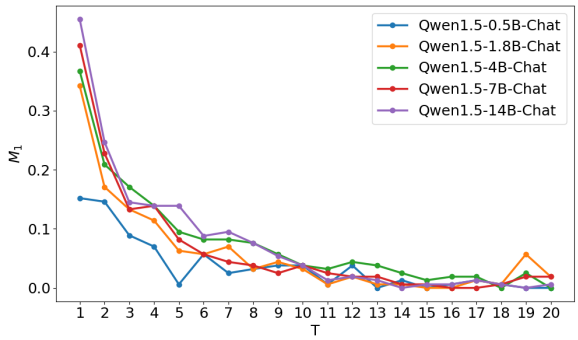

Figure 8: Forgetting of llms over longer time spans.

logue density on memory performance. As shown in Figure 7, it is more challenging for the model to remember a large amount of dialogue information at once and maintain memory persistence. When the model remembers dialogues with 20 users at once, the M1 at T1 is 0.420, which is 48.4% higher than for 100 users (M1 is 0.283). At T6, the M1 for 20-user dialogues (0.15) is 354.5% higher than the M1 for 100-user dialogues (0.033).

Do llms completely forget?

Tirumala et al. (2022) found that models have a forgetting baseline, meaning there is a lower limit to the forgetting curve. This baseline increases with model size, suggesting that increasing model size can mitigate forgetting. Inspired by this, we divided LOCCO into 20 time periods to observe the memory retention of large language models over longer intervals. The experimental results are shown in Figure 8.

Contrary to the observations in Tirumala et al. (2022), for long-term dialogue memory, large language models tend to almost completely forget the initial dialogue content after a sufficiently long interval, with no memory baseline. Increasing model size does not effectively alleviate long-term forgetting. In Tirumala et al. (2022), memory is measured by the model's prediction accuracy for each context in the training data (including missing text blocks and words). If a model can accurately predict missing words, it is considered to have memorized the context. We believe that even if a model hasn't memorized a specific context, it can still infer based on existing knowledge and language structure. This could lead to correct word predictions despite forgetting all information, possibly forming a forgetting baseline. However, by designing more complex Q&A tasks, our approach ensures that once the model forgets specific information mentioned in historical dialogues, it cannot accurately answer using existing knowledge or reasoning. This avoids the aforementioned issue, making our conclusions more reliable.

Impact of Repetition on Memory.

Inspired by replay strategies in continual learning (see "A continual learning survey: Defying forgetting in classification tasks") and repetition phenomena in humans ("The right time to learn: mechanisms and optimization of spaced learning," "Effects of spaced retrieval training on semantic memory in Alzheimer's disease: A systematic review," "Expanding retrieval practice promotes

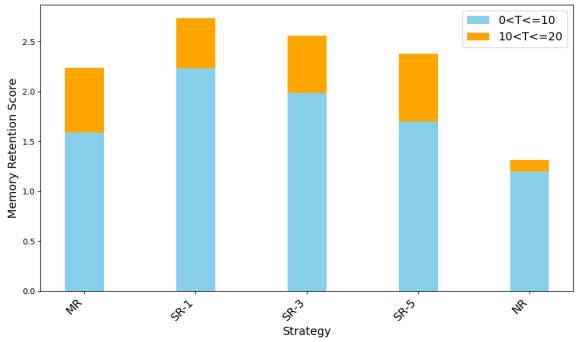

Figure 9: The impact of different repetition strategies on memory across various time ranges. MR represents Massed Repetition, SR-N represents repetition every N time periods, and NR represents no repetition. The model used is Qwen1.5-7B-Chat. We sum M1 for the time ranges $0 < T \leq 10$ and $10 < T \leq 20$.

short-term retention, but equally spaced retrieval enhances long-term retention") and neural network models ("Repeat before forgetting: Spaced repetition for efficient and effective training of neural networks"), we designed the following repetition strategies:(1)Massed Repetition: After training on D1, conduct three additional training sessions; (2)Spaced Repetition: Repeat D1 within the first 10 time periods, with intervals of 1, 3, and 5 periods. Repetition is only within the first 10 periods to observe its impact on memory during and after the repetition period.

We use Memory Retention Score to measure the impact of repetition on memory: summing M1 over a specific time range represents the total memory capacity within that range. A higher score indicates stronger memory retention, as shown in Figure 9.

We found that repetition within the first 10 periods enhances memory across the entire time range, particularly in the $10 < T \leq 20$ range, showing a clear advantage over NR. Furthermore, models using the SR-3 strategy outperform MR in all time ranges. Despite both undergoing three repetitions, spaced repetition is more effective than massed repetition.

5 Conclusion

To explore the long-term memory of llms, we developed an automated pipeline, LoCoGen, for constructing long-term dialogue data and created the LOCCO dataset, which includes long-term dialogue data between 100 users and a chatbot, along with QA pairs to evaluate model memory. Experiments show that llms can remember historical interaction information with users to some extent, but this memory gradually weakens over time, especially when dealing with very long time spans. We also revealed that models have preferences when remembering different categories of information, providing a new direction for future research on how to balance and optimize memory capabilities for different types of information. Additionally, we found that repetition strategies can effectively improve the persistence of model memory. Our research not only provides new methods and datasets for evaluating the long-term memory capabilities of llms but also offers important references and insights for future improvements in the persistence and accuracy of model memory. Future work can further explore improvements in model architecture and training methods to better support long-term memory retention and application.

Limitations

Dataset Size and Diversity: Although the LOCCO dataset includes long-term dialogues from 100 users, these dialogues are generated by large language models and may lack the diversity and complexity of real user interactions. Future research could incorporate more real-world data to validate the generalizability of the results. Additionally, we used closed-source models for data generation, meaning we accessed the most powerful commercial LLMs through paid APIs.

Model Parameter Limitations: Our experiments focused mainly on large language models of specific parameter sizes. Due to equipment constraints, it was challenging to analyze models with larger parameter sizes. Moreover, we evaluated only a subset of open-source large language models, and a broader evaluation would require substantial time investment. Further research should test a wider range of model parameters.

Limitations of Evaluation Metrics: We used consistency models to assess response accuracy, which may not fully reflect the model's memory capabilities. A good dialogue system needs not only to remember historical information but also to use it to perform more complex tasks. Setting more comprehensive evaluation metrics is challenging, and we will strive to improve this in the future.

Language: Our pipeline for generating long-term dialogues based on LLMs was developed only for English. However, our pipeline can be adapted for any other language using proficient LLMs and

appropriate translations of our prompts.

Training Setup: We explored optimal experimental parameters through preliminary experiments. Due to limitations in computational resources and time, we could not conduct comprehensive experiments on all possible parameter settings. However, we ensured the reasonableness and validity of the experimental results by maintaining consistency in experimental parameters.

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A LoCoGen for LOCOMO

A.1 Prompts

We used GPT-4o in LoCoGen to construct data, as it is one of the most powerful models currently available. For each step in LoCoGen, we initially conducted small-batch generations and manually checked the data quality, adjusting prompts to enhance the quality of the generated data. Figure 10-15 provide the prompts used in different steps, and Table 2 shows an example of a long-term conversation.

Please create fictional character situations at three different time points (1 year ago, 3 years ago, 5 years ago) based on the character information provided below.

Use brief sentences to describe each time point's character situation.

Each time point must contain unique information and should reflect the alternating development of new and old things (e.g., new hobbies, further development of old interests, formation of new relationships, personality changes, etc.).

The information should be appropriate for the character's age at that time. Please describe information ("hobby", "personality", "family_relationship", "social_relationship", "study_or_work_status") in a concise paragraph:

{Character information}

Figure 10: Prompts for extending character descriptions.

Below are two character profiles from different points in time.
Please insert {N} additional profiles at different points in time between the given profiles, showcasing the progression and alternation of new and old elements (such as developing new hobbies, furthering existing interests, forming new relationships, personality changes, etc.). The profiles must fit the character's age at that time, demonstrating their development and changes to make the transitions more natural and complete. Only reply with {N} character profiles.

{Time 1 information; Time 2 information}

Figure 11: Prompts for obtaining more detailed character descriptions.

Please generate {n} coherent diary entries for the character based on the following information, with each entry occurring between the specified two time points. Each diary entry should include a date and content, and refer to the context provided to ensure coherence and consistency.
{
[Part 1: Background Information]
{Structured Data List}
[Part 2: Descriptions of specified two time points]
time1 describe:{time1 describe}
time2 describe:{time2 describe}
[Part 3: Summaries of previous diary entries]
{diaries summary}
[Part 4: Recent Diary Conten]
{last stage diaries}
}

When generating new diary entries, please follow these requirements:
{
1. Each diary entry's time point should be evenly distributed between [time1 describe] and [time2 describe].
2. The diary content should reflect the character's changes and development from time point 1 to time point 2.
3. The diary content must not conflict with the Background Information, Summaries of previous diary entries, and Recent Diary Content.
4. Each diary entry must describe a specific event, and any mentioned locations, people, or items must have specific names.
}

Figure 12: Prompts for inserting multiple events.

Please construct a multi-turn dialogue (3-5 rounds) record between a user and a chatbot based on the following the user's diary entry, with the conversation occurring at the same time as described in the diary:
{the event}
Requirements:
1. The Chatbot's responses should be conversational, logically clear, and varied.
2. The format must refer to:{formatted_data}
3. The chat must be coherent, brief and natural.

Figure 13: Prompts for generating dialogues between the user and the chatbot.

Author's past situation:
{past_elements}
Author's recent diary:
{
{events content}
}
Please update the [author's past situation] based on the [author's recent diary], ensuring the content is updated with specific descriptions for each item. For content that has changed(educational background, emotional status), keep only the most recent one.
Please output in JSON format, including [social circle list, family relationship list, study or work progress, educational background, emotional status].

Figure 14: Prompts for automatically updating the structured data list.

Please read the following diary contents and summarize all the key information from the diaries. Remove any invalid or redundant expressions, retaining only the core content of each diary. The diary contents are as follows:
{
{Events content}
}
Please output a paragraph summarizing what is discussed in all the diaries. Must be less than 500 words.

Figure 15: Prompts for summarizing event content.

Check whether the conversation data meets the following conditions. If yes, output Yes; otherwise, output No:
1. Incomplete conversations: Any missing or incomplete conversation records should be filtered out.
2. Noisy conversations: Any conversations that contain obvious noise, such as typos, grammatical errors, or non-verbal characters, should be filtered out to improve data quality and model training efficiency.
{conversation data}

Figure 16: Prompt for Dialogue Filtering.

A.2 Quality

To ensure consistent quality in LOCCO, we filtered out the following cases: (1) Dialogue data with missing or incomplete records were removed. (2) Dialogues containing excessive noise (such as spelling errors, grammatical mistakes, non-linguistic characters, etc.) were filtered out to enhance data quality and model training effectiveness. We used GPT-4o to inspect the dialogues, with specific prompts shown in Figure 16.

Context:
You are an evaluator tasked with assessing the quality of a conversation between a user and a chatbot. You need to rate the conversation based on three metrics: Participation, Coherence, and Rationality.

Instructions:
Participation: Rate how actively and meaningfully both parties (user and chatbot) engage in the conversation. Consider the relevance and contribution of each turn in the dialogue.
Coherence: Evaluate the logical flow and consistency of the conversation. The dialogue should make sense as a whole, with each response appropriately following the preceding interaction.
Rationality: Assess the reasonableness and sensibility of the chatbot's responses. The responses should be logical, well-founded, and appropriate given the context of the conversation.

For each metric, provide a score on a scale from 1 to 5, where 1 is very poor and 5 is excellent.

Example Conversation: {The Conversation}

Evaluation Format:
{
"Participation": [Your Score],
"Coherence": [Your Score],
"Rationality": [Your Score]
}

Figure 17: The prompt used for evaluating conversations.

A.3 Evaluation

We evaluated the dialogue data in terms of engagement, coherence, and plausibility. We found that data constructed by large models were of high quality. Figure 17 shows the prompts used for evaluation, and Table 2 presents the evaluation results.

The current time is {Currant Time}.
The following is a historical conversation between the user and the chatbot: {A history conversation}

Task: Please choose a key piece of information from the historical conversation (e.g., the name of an event, a person's name, a location, etc.), and then construct a question and answer pair between the user and the chatbot based on that key information. In the question, the user needs to provide a detailed and specific description to ensure the answer is clear and precise, guiding the chatbot to provide an accurate response based on the historical conversation.
The chatbot must use the key information mentioned in the historical conversation as part of its reply.

Please output a structured JSON object following this format:{"User": "A detailed, accurate question.","Chatbot": "Response."}

Figure 18: Prompts for Generating Dialogue QA Pairs.

B Dialogue QA Data

B.1 Generating dialogue QA pairs

Specifically, we instructed the large language model to first select a key piece of information from the dialogue and then construct a dialogue QA pair between the user and the chatbot based on this information. Key information includes names, locations, event names, etc., which are considered crucial points in the dialogue worth remembering long-term by the model. The prompts used for generating dialogue QA pairs are shown in Figure 18.

B.2 Filtering Rules

We removed QA pairs that did not meet the criteria based on the following two rules: Rule 1: The question is ambiguously phrased, leading to multiple reasonable answers. In other words, the question does not provide enough clear information, making it impossible to ensure a uniquely correct model response. Rule 2: The key information required for the answer comes from multiple different dialogue fragments. The model must rely on key information from the corresponding historical dialogue in the QA pair to answer, otherwise, it does not meet our evaluation goals.

#Instruction#
I am [Gabrielle Johnson], we had a chat, please recall the chat that happened on [2017-04-28].

#Output#
[
Gabrielle Johnson: Just finished at drama club. We′ re working on a new play!
Assistant: That sounds really exciting! Are you aiming for a major role?
Gabrielle Johnson: Yep, I'm hoping to get a major role again. Fingers crossed!
Assistant: I'll be rooting for you! Did you get positive vibes from your first read-through?
...
]

Figure 19: Data Format for Training Historical Dialogues.

C Training Example

To explore whether training can enable large models to remember historical dialogues, we need to construct a reasonable data format, which is different from improving the model's dialogue capability. We used supervised fine-tuning to help the large model remember dialogues with the user. Specifically, we included the character's name and dialogue timestamp as part of the instructions and used the dialogue content as labels. Specific training examples are shown in Figure 19.

#Example1:# I am .... Question: {User Question}

#Example2:# I am .... Question: {User Question}

#Example3:# I am .... Question: {User Question}

I am {NAME}, and the current time is {TIME}. You need to accurately recall our historical conversation , and use the information mentioned in the historical conversation to answer the question. Question: {User Question}

Figure 20: Prompts for Testing Model Memory.

D Testing Example

We tested using a few-shot approach by providing the model with 3 additional correct dialogue QA examples. We found this method very effective for smaller parameter models, as their instruction-following capabilities might be insufficient to accurately comprehend test instructions. Figure 20 shows the specific prompt templates for testing memory.

Record of the conversation between the user and the chatbot: {A history conversation}
The current time is: {Currant Time}
Now, the user asks the chatbot a question to check if the chatbot remembers something mentioned in the record of the conversation:{Question}
The response of the chatbot is: {Response}
Please determine whether the response of the chatbot is accurate. If the response of the chatbot is consistent with the content in the record of the conversation, please output "Yes", otherwise output "No"."

Figure 21: Instructions for Training the Consistency Model.

E Consistency Model

When training the consistency model, we randomly selected 500 consistent responses from the QA data as positive samples and used GPT-4o to generate 500 inconsistent responses as negative samples. The dataset was split into training and validation sets in an 8:2 ratio. Training was conducted according to the instructions in Figure 21. We used Qwen1.5-4B-Chat as the pre-trained model and adopted LoRA (Low-Rank Adaptation) for training. The training process used a batch size of 4, with rank and alpha set to 128 and 256, respectively, and a learning rate of 1.0e-4, continuing for 2 epochs. A cosine annealing learning rate schedule was employed, with a 10% warm-up ratio at the beginning. Our Consistency Model achieved an accuracy of 98% on the validation set.

Please categorize the answers to the questions. Categories need to be selected from ["people", "date and time", "location", "event", "emotions", "entity"]. You only need to output the category of the answer information.
[
{Question}
Answer:{Answer}
]
Class:

Figure 22: Prompts for classifying key information.

F Classifying Information

Figure 22 shows the prompts used for classifying key information involved in the dialogue QA pairs. Table 3 displays the percentage and number of QA pairs for different categories. For categories with fewer instances, the test results may not be representative, and we merged them into the "Others" category.

Metrics	Avg	Std
Participation	4.21	0.77
Coherence	4.15	0.96
Rationality	4.42	1.02
Overall	4.26	-

Table 2: GPT-4o evaluation for the quality of LOCCO.

Category	Percentage	Quantity
Name	23.60%	704
Location	18.80%	560
Event	37.60%	1121
Others	20%	596

Table 3: Distribution of different categories.