Recommender AI Agent: Integrating Large Language Models for Interactive Recommendations

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Abstract Recommender models excel at providing domain-specific

item recommendations by leveraging extensive user behavior data. Despite their ability to act as lightweight domain experts, they struggle to perform versatile tasks such as providing explanations and engaging in conversations. On the other hand, large language models (LLMs) represent a significant step towards artificial general intelligence, showcasing remarkable capabilities in instruction comprehension, commonsense reasoning, and human interaction. However, LLMs lack the knowledge of domain-specific item catalogs and behavioral patterns, particularly in areas that diverge from general world knowledge, such as online e-commerce. Finetuning LLMs for each domain is neither economic nor efficient. In this paper, we bridge the gap between recommender models and LLMs, combining their respective strengths to create a versatile and interactive recommender system. We introduce an efficient framework called InteRecAgent, which employs LLMs as the brain and recommender models as tools. We first outline a minimal set of essential tools required to transform LLMs into InteRecAgent. We then propose an efficient workflow within InteRecAgent for task execution, incorporating key components such as a memory bus, dynamic demonstration-augmented task planning, and reflection. InteRecAgent enables traditional recommender systems, such as those ID-based matrix factorization models, to become interactive systems with a natural language interface through the integration of LLMs. Experimental results on several pub-

1 Introduction

lic datasets show that InteRecAgent achieves satisfying per-

formance as a conversational recommender system, outper-

Recommender systems (RSs) have become an essential component of the digital landscape, playing a significant role in helping users navigate the vast array of choices available across various domains such as e-commerce and entertainment. By analyzing user preferences, historical data, and contextual information, these systems can deliver personalized recommendations that cater to individual tastes. Over the years, recommender systems have evolved from simple collaborative filtering algorithms to more advanced hybrid approaches that integrate deep learning techniques.

forming general-purpose LLMs.

However, as users increasingly rely on conversational interfaces for discovering and exploring products, there is a growing need to develop more sophisticated and interactive recommendation systems that can understand and respond effectively to diverse user inquiries and intents in an conversational manner.

Large language models (LLMs), such as GPT-3 (Brown et al. 2020) and PaLM (Chowdhery et al. 2022), have made significant strides in recent years, demonstrating remarkable capabilities in artificial general intelligence and revolutionizing the field of natural language processing. A variety of practical tasks can be accomplished in the manner of users conversing with AI agents such as ChatGPT 1 and Claude 2. With their ability to understand context, generate humanlike text, and perform complex reasoning tasks, LLMs can facilitate more engaging and intuitive interactions between users and RSs, thus offering promising prospects for the next generation of RSs. By integrating LLMs into RSs, it becomes possible to provide a more natural and seamless user experience that goes beyond traditional recommendation techniques, fostering a more timely understanding of user preferences and delivering more comprehensive and persuasive suggestions.

Despite their potential, leveraging LLMs for recommender systems is not without its challenges and limitations. Firstly, while LLMs are pretrained on vast amounts of textual data from the internet, covering various domains and demonstrating impressive general world knowledge, they may fail to capture fine-grained, domain-specific behavior patterns, especially in domains with massive training data. Secondly, LLMs may struggle to understand a domain well if the domain data is private and less openly accessible on the internet. Thirdly, LLMs lack knowledge of new items released after the collection of pretraining data, and finetuning with up-to-date data can be prohibitively expensive. In contrast, in-domain models can naturally address these challenges. A common paradigm to overcome these limitations is to combine LLMs with in-domain models, thereby filling the gaps and producing more powerful intelligence. Notable examples include AutoGPT ³, HuggingGPT(Shen

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¹https://chat.openai.com/

²https://claude.ai/

³https://github.com/Significant-Gravitas/Auto-GPT

et al. 2023), and Visual ChatGPT(Wu et al. 2023). The core idea is to utilize LLMs as the "brains" and in-domain models as "tools" that extend LLMs' capabilities when handling domain-specific tasks.

In this paper, we adopt a similar approach, aiming to leverage the strengths of both LLMs and recommendation models for conversational recommender systems. We propose InteRecAgent (Interactive Recommender Agent), a system explicitly designed to cater to the specific requirements and nuances of recommender systems, thereby establishing a more effective connection between the LLM's general capabilities and the specialized needs of the recommendation domain. To achieve this, we develop a compact framework comprising three distinct sets of tools, designed to transform users' inquiries into a sequence of tool executions within the framework. Given the typically large number of item candidates, storing the tools' input and output as observations in the prompt is impractical. Therefore, we introduce a shared memory bus strategy to store intermediate states and facilitate communication between tools. To ensure that LLMs can specify the correct execution path of tools, we propose a dynamic demonstration-augmented plan-first execution strategy. Unlike the step-by-step strategy employed by ReAct (Yao et al. 2022), InteRecAgent generates all the steps of tool-calling at once and strictly follows the execution plan to accomplish the task. During the conversation, InteRecAgent parses the user's intent and retrieves a few demonstrations that are most similar to the current intent. These dynamically retrieved demonstrations help LLMs formulate a correct task execution plan. Lastly, we implement a reflection strategy, wherein another LLM acts as a critic to evaluate the quality of the results and identify any errors during the task execution. If the results are unsatisfactory or errors are detected, InteRecAgent reverts to the initial state and repeats the plan-then-tool-execution process. This iterative approach ensures that InteRecAgent delivers high-quality recommendations while effectively addressing the challenges associated with integrating LLMs into RSs.

Our main contributions are summarized as follows:

- We propose InteRecAgent, a compact framework that democratizes conversational recommender systems by integrating LLMs with three distinct sets of traditional recommendation models.
- To ensure an effective combination of LLMs and recommenders, we further introduce a shared memory bus, a dynamic demonstration-augmented plan-first execution strategy, and a reflection strategy within InteRecAgent.
- Experimental results from three public datasets demonstrate the effectiveness of InteRecAgent, with particularly significant advantages in domains that are less covered by world knowledge.

2 Related Work

2.1 Conversational Recommender System

Existing researches in conversational recommender systems (CRS) can be primarily categorized into two

main areas (Gao et al. 2021): attribute-based questionanswering (Zou and Kanoulas 2019; Zou, Chen, and Kanoulas 2020; Xu et al. 2021) and open-ended conversation (Li et al. 2018; Wang et al. 2022b, 2021). In attributebased question-answering CRS, the system aims to recommend suitable items to users within as few rounds as possible. The interaction between the system and users primarily revolves around question-answering concerning desired item attributes, iteratively refining user interests. Key research challenges in this area include developing strategies for selecting queried attributes(Mirzadeh, Ricci, and Bansal 2005; Zhang et al. 2018) and addressing the explorationexploitation trade-off(Christakopoulou, Radlinski, and Hofmann 2016; Xie et al. 2021). In open-ended conversation CRS, the system manages free-format conversational data. Initial research efforts in this area focused on leveraging pretrained language models for conversation understanding and response generation(Li et al. 2018; Penha and Hauff 2020). Subsequent studies incorporated external knowledge to enhance the performance of open-ended CRS(Chen et al. 2019; Wang, Su, and Chen 2022; Wang et al. 2022b). Nevertheless, these approaches struggle to reason with complex user inquiries and maintain seamless communication with users. The emergence of LLMs presents an opportunity to revolutionize the construction of conversational recommender systems, potentially addressing the limitations of existing approaches and enhancing the overall user experience.

2.2 Enhancing LLMs

The scaling-up of parameters and data has led to significant advancements in the capabilities of LLMs, including incontext learning (Brown et al. 2020; Liu et al. 2021; Rubin, Herzig, and Berant 2021), instruction following (Ouyang et al. 2022; Touvron et al. 2023a; OpenAI 2023), and planning and reasoning (Wei et al. 2022; Wang et al. 2022a; Yao et al. 2022; Yang et al. 2023; Wang et al. 2023). In the domain of recommender systems, the application of LLMs is becoming a rapidly growing trend (Liu et al. 2023; Dai et al. 2023; Kang et al. 2023; Wang and Lim 2023).

As models with general intelligence and natural language processing capabilities, LLMs inevitably lack domainspecific skills, such as editing images or answering questions in specialized domains. To compensate for these weaknesses, researchers have started exploring the use of external tools to augment LLMs' abilities (Qin et al. 2023). For example, (Nakano et al. 2021; Shuster et al. 2022) have equipped LLMs with a web search engine, allowing initially offline LLMs to access online resources. Others have employed mathematical calculation tools to enhance LLMs' mathematical abilities (Schick et al. 2023; Thoppilan et al. 2022) and improve coding capabilities with a Python interpreter (Gao et al. 2023; Chen et al. 2022). To integrate vision capabilities, Visual ChatGPT (Wu et al. 2023) and Hugging-GPT (Shen et al. 2023) have incorporated visual models as tools, enabling LLMs to generate and process images. To the best of our knowledge, this paper is the first to explore the LLM + tools paradigm in the field of recommender systems.

3 Methodologies

3.1 The Overall Framework

The comprehensive framework of InteRecAgent is depicted in Figure 1. Fundamentally, LLMs function as the brain, while recommendation models serve as tools that supply domain-specific knowledge. Users engage with an LLM using natural language. The LLM interprets users' intentions and determines whether the current conversation necessitates the assistance of tools. For instance, in a casual chitchat, the LLM will respond based on its own knowledge; whereas for in-domain recommendations, the LLM initiates a chain of tool API calls and subsequently generates a response by observing the execution results of the tools. Consequently, the quality of recommendations relies heavily on the tools, making the composition of tools a critical factor in overall performance. To ensure seamless communication between users and InteRecAgent, covering both casual conversation and item recommendations, we propose that a minimum set of tools should encompass the following aspects:

- Information Query. During conversational interactions, the InteRecAgent not only handles item recommendation tasks but also frequently addresses users' inquiries. For example, within a gaming platform, users may ask questions like, "What is the release date of this game and how much does it cost?" To accommodate such queries, we have equipped the LLMs with an item information query module. This module can efficiently retrieve detailed item information from the backend item information database using Structured Query Language (SQL) expressions.
- Item Retrieval. Retrieval tools aim to propose a list of item candidates that satisfy a user's intent within the current conversation. These tools can be compared to the retrieval stage of a practical recommender system, which serves to narrow down relevant candidates to a smaller list for large-scale serving. In InteRecAgent, we consider two types of demands that a user may express in their intent: hard conditions and soft conditions. Hard conditions refer to explicit demands on items, such as "I want some popular sports games." or "Recommend me some RPG games under \$100." Soft conditions pertain to demands that cannot be explicitly expressed with discrete attributes and require the use of semantic matching models, like "I want some games similar to Call of Duty and Fortnite." It is essential to incorporate multiple tools to address both conditions. Consequently, we utilize an SQL tool to handle hard conditions, finding candidates from the item database. For soft conditions, we employ an item-toitem tool that matches similar items based on latent embeddings.
- Item Ranking. Ranking tools play a crucial role in tailoring personalized content for users by taking into account their historical data and preferences expressed during conversations. The ranking module is designed to analyze a user's history and specific interests mentioned throughout the dialogue, using this information as input to prioritize items within the candidate set. This process ensures that the recommendations provided are not only relevant to the user's current intent but also align with their overall

preferences and tastes. By effectively ranking items, InteRecAgent can deliver a more engaging and satisfying user experience, enhancing the overall effectiveness of the recommendation system.

LLMs have the potential to handle various user inquiries when supplemented with these diverse tools. For instance, a user may ask, "I've played Fortnite and Call of Duty before. Now, I want to play some puzzle games with a release date after Fortnite's. Do you have any recommendations?" In this scenario, the tool execution sequence would be "SQL Query $Tool \rightarrow SQL$ Retrieval $Tool \rightarrow Ranker Tool$." First, the release date of Fortnite is queried, then the release date and puzzle genre are interpreted as hard conditions for the SQL retrieval. Finally, Fortnite and Call of Duty are considered as the user profile for the ranking model.

Typically, the tool augmentation is implemented via Re-Act (Yao et al. 2022), where LLMs generate reasoning traces, actions, and observations in an interleaved manner. We refer to this style of execution as *step-by-step*. Our initial implementation also employed the step-by-step approach. However, we soon observed some limitations due to various challenges. Firstly, retrieval tools may return a large number of items, resulting in an excessively long observation prompt for LLMs. Additionally, including numerous entity names in the prompt can degrade LLMs performance. Secondly, despite their powerful intelligence, LLMs may use tools incorrectly to complete tasks, such as selecting the wrong tool to call or omitting key execution steps. To address these challenges, we propose the following mechanisms:

- Candidate Memory Bus. We allocate a separate memory to store the current item candidates, eliminating the need to append them to prompt inputs. All tools can access and modify the candidate memory.
- Plan-first Execution with Dynamic Demonstrations. Rather than using the *step-by-step* approach, we adopt a two-phase method. In the first phase, we compel the LLM to formulate a comprehensive tool execution plan in one attempt based on the user's intention derived from the dialogue. In the second phase, the LLM strictly adheres to the plan, calling tools in sequence while allowing them to communicate via the Candidate Memory Bus. In order to enable the LLM to devise more rational plans, we employ a dynamic demonstration strategy for in-context learning. Specifically, we first generate various possible forms of user intent and the corresponding execution plans. When addressing a user's intention, we retrieve the most similar examples of intent from these samples and incorporate them as demonstrations into prompt.
- **Reflection.** After the planned execution is completed, we allow LLMs to reflect on the observations to identify any exceptions (e.g., poor result quality or errors raised due to data format failures). If necessary, InteRecAgent will initiate another chain of $\langle \text{plan}, \text{execution} \rangle$ processes, providing LLMs with additional opportunities to generate high-quality answers, which is called *rechain*.

In the following sections, we will provide detailed introductions to the three mechanisms.

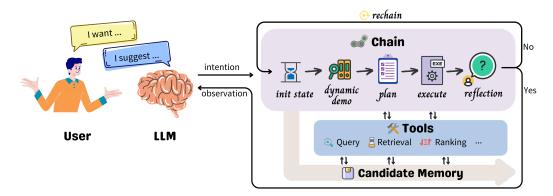


Figure 1: InteRecAgent Framework. LLM plays the role of the brain to parse user intentions and generate responses. *Italic text* represents actions, while regular text represents information.

3.2 Candidate Memory Bus

The large number of items can pose a challenge when attempting to include items generated by tools in prompts as observations for the LLM, due to input context length limitations. Meanwhile, the input of a subsequent tool often depends on the output of preceding tools, necessitating effective communication between tools. Thus, we designed a Candidate Memory Bus to facilitate the circulation of candidate items among tools. The Memory Bus, accessible by all tools, comprises two parts: a data bus for storing candidate items, and a tracker for recording each tool's output.

The candidate items in the data bus are initialized to include all items at the beginning of each conversation turn by default. At the start of each tool execution, candidate items are read from the data bus, and the data bus is then refreshed with the filtered items at the end of each tool execution. This mechanism allows candidate items to flow sequentially through the various tools in a streaming manner. Notably, users may explicitly specify a set of candidate items in the conversation, such as "Which of these movies do you think is most suitable for me: [Movie List]?" In this case, the LLM will call a special tool—the memory initialization tool—to set the user-specified items as the initial candidate items.

The tracker within the memory serves to record tool execution. Each tool call record is represented as a triplet (f_k, o_k) , where f_k denotes the name of the k-th tool, and o_k is the output of the tool's execution, such as the number of remaining candidates, runtime errors. The tracker's main function is to aid the critic in making judgments within the reflection mechanism, acting as the o^t in reflect (\cdot) , as described in Section 3.4.

With the help of the Candidate Memory Bus component, items can be transmitted in a streaming manner between various tools and continuously filtered according to conditions, presenting a funnel-like structure for the recommendation process. The tracker's records can be considered as short-term memory for further reflection.

3.3 Plan-first Execution with Dynamic Demonstrations

In conversational scenarios, a key challenge is how to enable LLM to specify the correct tool execution path to han-

dle diverse user's intentions. Unlike the *step-by-step* strategy employed in ReAct, we introduce a two-phase approach that enables LLM to make a tool execution plan at once and then strictly follow the plan to accomplish the task, which is called plan-first execution. We summarize the differences between our plan-first execution strategy and ReAct in Appendix and demonstrate the superiority of our strategy through experiments. Concretely, the plan-first execution consists of the following two phases.

- Plan: LLM accepts the user's current input x^t , dialogue context C^{t-1} , descriptions of various tools \mathcal{F} , and demonstration \mathcal{D}_{x^t} for in-context learning. LLM formulates a tool usage plan based on user intent and preferences, providing inputs for each tool, i.e., $p^t = \{p_1^t, \cdots, p_n^t\} = \text{plan}(x^t, C^{t-1}, \mathcal{F}, \mathcal{D}_{x^t})$, where $p_k^t = (f_k, i_k)$ consists of the tool f_k and its input i_k .
- Execution: The tool executor invokes the tools step-by-step according to the plan p_t and obtains outputs from each tool, i.e., $o^t = \{o_1^t, \cdots, o_n^t\} = \text{exec}(p^t, \mathcal{F})$. The output feedback of each tool f_k is defined as o_k^t , where only the item information o_n^t from the last tool's output serves as LLM's observation for generating the response y^t . The remaining information is tracked by the candidate memory bus for further reflection (see Section 3.4).

In order to improve the planning capability of LLM, demonstrations \mathcal{D}_{x^t} are injected into prompts for in-context learning in the **Plan** phase. Each demonstration consists of a user intent x and tool execution path p. However, the number of demonstrations is strictly limited by the contextual length that LLM can process, which makes the quality of demonstrations of paramount importance. To address the challenge, we introduce a dynamic demonstration strategy, where only a few demonstrations that are most similar to current user intent are incorporated into the prompt. For example, if the current user input is "My game history is Call of Duty and Fortnite, please give me some recommendations", then demonstration with user intent "I enjoyed ITEM1, ITEM2 in the past, give me some suggestions" may be retrieved as a high-quality demonstration. Inspired by Self-Instruct (Wang et al. 2022a), we leverage LLM to generate hundreds of demonstrations to obtain more user intent and execution path. Both input-first and output-first strategy proposed in Self-Instruct are used in demonstration generation, and details are given in Appendix. Since the execution path being solely related to the user's intent format but not specific items or attributes, we restricted the generation by using placeholders such as ITEM and TYPE to substitute for specific item and attributed. This trick ensures that the retrieval focuses on the structure of user intent without being influenced by the specific details.

3.4 Reflection

Despite LLM's strong intelligence, it still exhibits occasional errors in reasoning and tool utilization (Madaan et al. 2023; Shinn et al. 2023). For example, it may violate instructions in the prompt by selecting a non-existent tool, omit or overuse some tools, or fail to prepare tool inputs in the proper format, resulting in errors in tool execution.

To reduce the occurrence of such errors, some studies have employed self-reflection (Shinn et al. 2023) mechanisms to enable LLM to have some error-correcting capabilities during decision-making. In InteRecAgent, we utilize an **actor-critic** reflection mechanism to enhance the agent's robustness and the error-correcting ability. In the following part, we will formalize this self-reflection mechanism.

Assume that in the t-th round, the dialogue context is C^{t-1} and the current user input is x^t . The actor is a LLM equipped with tools and inspired by the dynamic demonstration-augmented plan-first execution mechanism. For the user input, the actor would make a plan p^t , obtain the tools' output o^t and generate the response y^t . The critic evaluates the behavioral decisions of the actor. The execution steps of the reflection mechanism are listed as follows:

- Step1: The critic evaluates the actor's output p^t , o^t and y^t under the current dialogue context and obtains the judgment $\gamma = \operatorname{reflect}(x^t, C^{t-1}, p^t, o^t, y^t)$.
- Step2: When the judgment γ is positive, it indicates that the actor's execution and response are reasonable, and the response y^t is directly provided to the user, ending the reflection phase. When the judgment γ is negative, it indicates that the actor's execution or response is unreasonable. The feedback γ is used as a signal to instruct the actor to rechain, which is used as the input of $\operatorname{plan}(\cdot)$.

In the actor-critic reflection mechanism, the actor is responsible for the challenging plan-making task, while the critic is responsible for the relative simple evaluation task. The two agents cooperate on two different types of tasks and mutually reinforce each other through in-context interactions. This endows InteRecAgent with enhanced robustness to errors and improved error correction capabilities, culminating in more precise tool utilization and recommendations.

3.5 Dialogue Compression

Employing the LLM as a conversational module encounters another considerable challenge: the incongruity between the increasing dialogue length and the fixed contextual length limit of LLM's input. This issue is particularly prominent in tool learning, where a specific number of tokens are necessitated for the description of tasks and tools. In InteRecAgent,

we leverage a LLM to compress the dialogue once the length of dialogue reaches the limit.

4 Experiments

4.1 Experimental Setup

Evaluation Strategies. Evaluating conversational recommender systems presents a challenge, as the seeker communicates their preferences and the InteRecAgent provides relevant recommendations through natural, open-ended dialogues. To enable the quantitative assessment of InteRecAgent, we have designed two evaluation strategies:

User Simulator. We have designed a role-playing prompt to guide GPT-4 in simulating users interacting with conversational recommendation agents. A user's historical behavior is integrated into the prompt as their profile, with the last item in their history serving as the target item they wish to find. In this manner, GPT-4 behaves from the user's perspective and promptly responds to the recommended results, creating a more realistic dialogue scenario. This strategy is employed to evaluate the performance of InteRecAgent in multi-turn dialogue settings.

One-Turn Recommendation. Following the settings of traditional conversational recommender systems on ReDial (Li et al. 2018), we incorporate the one-turn recommendation strategy: given a user's history, we design a prompt that enables GPT-4 to generate a dialogue, simulating the communication between a user and a rec-agent. The goal is to test whether a rec-agent can accurately recommend the ground truth item in the next response. We evaluate both entire space retrieval and candidate-provided ranking tasks. Specifically, the dialogue context is supplied to the recommendation agent, along with the instruction Please give me k recommendations based on the chat history for retrieval task, and the instruction Please rank these candidate items base on the chat history for ranking task.

The prompts used in user simulator and one-turn recommendation can be found in the Appendix.

Dataset. To evaluate the effectiveness of our methods across different domains, we conduct experiments using three datasets: Steam⁴, MovieLens⁵ and Amazon Beauty⁶. Each dataset comprises user-item interaction history data and item metadata. We apply the leave-one-out method to divide the interaction data into training, validation, and testing sets. The training of all utilized tools is performed on the training and validation sets. Due to budget constraints, we randomly sample 100 and 500 instances from the testing set for user simulator and one-turn benchmarking respectively.

Baselines. As dialogue recommendation agents, we compare our methods with several general LLMs, including four open-source and two closed-source LLMs.

- Random: Sample k items uniformly from item set.
- **Popularity**: Sample k items according to the item popularity distribution.

⁴https://github.com/kang205/SASRec

⁵https://grouplens.org/datasets/movielens/10m

⁶http://jmcauley.ucsd.edu/data/amazon/links.html

- Llama-2-7B-chat, Llama-2-13B-chat (Touvron et al. 2023b): The 2nd version of the Llama released by Meta.
- Vicuna-v1.5-7B, Vicuna-v1.5-13B (Chiang et al. 2023): Open-source models fine-tuned with user-shared data from the ShareGPT⁷ based on Llama-2 series models.
- ChatGPT (gpt-3.5-turbo), GPT-4 (OpenAI 2023): SOTA LLMs from OpenAI.

For the Llama and Vicuna models, we employ the FastChat (Zheng et al. 2023) package to establish local APIs, ensuring their usage is consistent with ChatGPT and GPT-4.

Metrics. Since both our method and baselines utilize LLMs to generate response, which exhibit state-of-the-art text generation capabilities, our experiments primarily compare recommendation performance of different methods. For the user simulator strategy, we employ two metrics: $\operatorname{Hit}@k$ and $\operatorname{AT}@k$, representing the success of recommending the target item within k turns and the average turns (AT) required for a successful recommendation, respectively. When calculating $\operatorname{AT}@k$, unsuccessful recommendations within k rounds are recorded as k+1. In the one-turn strategy, we focus on the Recall@k and $\operatorname{NDCG}@k$ metric for retrieval and ranking task, respectively. In Recall@k, the k represents the retrieval of k items, whereas in $\operatorname{NDCG}@k$, the k denotes the number of candidates to be ranked.

Implementation Details. We employ GPT-4 as the brain of the InteRecAgent for user intent parsing and tool planing. Regarding tools, we use SQL as information query tool, SQL and ItemCF (Linden, Smith, and York 2003) as hard condition and soft condition item retrieval tools, respectively, and SASRec (Kang and McAuley 2018) without position embedding as the ranking tool. SQL is implemented with SQLite integrated in pandasq18 and retrieval and ranking models are implemented with PyTorch. The framework of InteRecAgent is implement with Python and LangChain⁹. For dynamic demonstration selection, we employ sentence-transformers¹⁰ to encode demonstrations into vectors and store them using ChromaDB¹¹, which facilitates ANN search during runtime. Regarding hyperparameter settings, we set the number of dynamic demonstrations to 3, the maximum number of candidates for hard condition retrieval to 1000, and the threshold for soft condition retrieval cut to the top 5%. The source code of InteRecAgent is released at https://aka.ms/recagent.

4.2 Evaluation with User Simulator

Table 1 presents the results of evaluations conducted using the user simulator strategy. Our method surpasses other LLMs in terms of both hit rate and average turns across the three datasets. These results suggest that our InteRecAgent is capable of delivering more accurate and efficient recommendations in conversations compared to general LLMs.

	Steam		n MovieLens			Beauty	
Methods	H@5↑	AT@5↓	H@5↑	AT@5↓	H@5↑	AT@5↓	
Llama2-7B	0.27	5.16	0.06	5.83	0.01	5.96	
Llama2-13B	0.31	5.04	0.28	5.22	0.00	6.00	
Vicuna-7B	0.22	5.35	0.15	5.69	0.00	6.00	
Vicuna-13B	0.25	5.16	0.38	5.11	0.05	5.89	
ChatGPT	0.41	4.76	0.64	4.14	0.07	5.80	
GPT-4	0.80	<u>2.85</u>	0.75	<u>4.05</u>	<u>0.16</u>	<u>5.54</u>	
Ours	0.83	2.53	0.85	3.10	0.60	3.72	

Table 1: Performance comparisons with the user simulator strategy. H@5 is an abbreviation for Hit@5.

Task	Retrieval(R@5↑)			Ranking(N@20↑)		
Dataset	Steam	Movie	Beauty	Steam	Movie	Beauty
Random	00.04 02.02	00.06	00.00	35.35	34.22	30.02
Popularity		01.61	00.08	36.06	34.91	31.04
Llama2-7B	13.54	05.85	06.71	07.30	04.59	03.03
Llama2-13B	14.14	15.32	07.11	21.56	18.05	15.95
Vicuna-7B	13.13	08.27	06.91	22.03	18.99	11.94
Vicuna-13B	18.18	16.13	07.52	30.50	24.61	18.85
ChatGPT	42.02	23.59	10.37	44.37	42.46	31.90
GPT-4	56.77	<u>47.78</u>	12.80	57.29	55.78	33.28
Ours	65.05	52.02	30.28	60.28	63.86	40.05

Table 2: Performance comparisons with LLMs in one-turn recommendation (%). R@5 and N@20 are abbreviations for Recall@5 and NDCG@20 respectively.

Overall, LLMs with larger parameter sizes perform better. ChatGPT and GPT4, with parameter sizes exceeding 100B, significantly outperform Llama2 and Vicuna-v1.5. 13B models from the same series almost always surpass 7B models, except for Llama2-7B and Llama2-13B, which both perform extremely poorly on the Beauty dataset.

Another interesting observation is the more significant improvement in relatively private domains, such as Amazon Beauty. In comparison to gaming and movie domains, the beauty product domain is more private, featuring a larger number of items not well-covered by world knowledge or being new. Table 1 reveals that ChatGPT and GPT-4 exhibit competitive performance in gaming and movie domains. However, in the Amazon Beauty domain, most LLMs suffer severe hallucination issue due to the extreme long and complex item names, resulting in a significant drop in performance. This phenomenon highlights the importance of our InteRecAgent in private domains.

4.3 Evaluation with One-Turn Recommendation

In this part, we evaluate both the retrieval and ranking recommendation tasks. For the *Retrieval* task, we set the recommendation budget k to 5 for all methods, with Recall@5 being the evaluation metric. For the *Ranking* task, we randomly sample 19 negative items, and together with the one positive item, they form the candidate list proactively provided by users. The evaluation metric for this task is NDCG@20.

⁷https://sharegpt.com/

⁸https://github.com/yhat/pandasql/

⁹https://www.langchain.com/

¹⁰ https://huggingface.co/sentence-transformers

¹¹ https://www.trychroma.com/

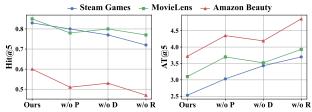


Figure 2: Ablation study under user simulator evaluation. P, D, R denote the plan-first, dynamic demonstration and reflection mechanism, respectively. Note that dynamic demonstration is also used in w/o P.

The results are shown in Table 2. Based on the results, we can draw conclusions similar to those in Section 4.2. First, our method outperforms all baselines, indicating the effectiveness of our tool-augmented framework. Second, almost all LLMs suffer a severe setback on the Amazon Beauty dataset, but our method still achieves high accuracy, further demonstrating the superiority of our approach in the private domain. Notably, some LLMs underperform compared to random and popularity methods in ranking tasks, particularly in the Amazon dataset. This can be primarily attributed to LLMs not adhering to the ranking instructions, which arise due to LLMs' uncertainty and produce out-of-scope items, especially for smaller LLMs.

4.4 Ablation Study

This paper introduces several key mechanisms to enhance LLM's ability to better utilize tools. To investigate their importance, we conduct ablation studies, with the results presented in Figure 2. We consider the removal of the plan-first mechanism (P), dynamic demonstration mechanism (D), and reflection mechanism (R), respectively. Experiments are carried out using the *user simulator* setting, as it provides a more comprehensive evaluation, encompassing both accuracy (hit rate) and efficiency (average turn) metrics.

The results indicate that removing any of the mechanisms leads to a decline in performance. Among these mechanisms, the removal of the reflection mechanism has the most significant impact on performance, as it can correct tool input format errors and tool misuse. Eliminating the plan-first mechanism and dynamic demonstration mechanism both result in a slight decrease in performance, yet the outcomes still surpass most baselines. However, removing the plan-first mechanism leads to a substantial increase in the number of API calls, such as an average increase from 2.78 to 4.51 per turn in the Steam dataset, resulting in an approximate 10-20 second latency increase.

4.5 Case Study

To effectively visualize InteRecAgent's performance, we present case studies in chit-chat and two domains: gaming and beauty products, as shown in Figure 3. We compare the outputs of GPT-4 and InteRecAgent for given user inputs.

In chit-chat scenario (Figure 3a), InteRecAgent retains the capabilities of GPT-4 while also possessing the added ability to query domain-specific data (such as the number of products), yielding more accurate information.

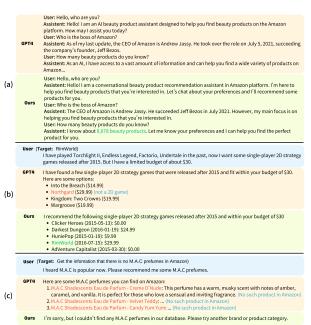


Figure 3: Case Study in (a) chit-chat, (b) Steam game domain and (c) Amazon Beauty e-commerce product domain.

In the game domain (Figure 3b), user input conditions are complex, encompassing user history and various demands. GPT-4's recommendations mostly align with conditions, except for a 3D game *Northgard* misidentified as 2D. InteRecAgent's response adheres to user conditions, and notably, includes the subsequent game in the user's historical sequence, *RimWorld*, owing to its superior ranking performance.

In the e-commerce domain (Figure 3c), GPT-4's hallucination phenomenon intensifies, resulting in giving products not existing in Amazon platform. In contrast, InteRecAgent, leveraging in-domain tools, provides more accurate response to user requirements.

5 Conclusion

In this paper, we introduce InteRecAgent, a compact framework that transforms traditional recommender models into intelligent and interactive systems by harnessing the power of LLMs. We identify a diverse set of fundamental tools, categorized into information query tools, retrieval tools, and ranking tools, which are dynamically interconnected to accomplish complex user inquiries within a task execution framework. To enhance task execution accuracy, we propose three novel modules: the candidate memory bus, dynamic demonstration-augmented plan-first execution, and reflection. Experimental findings demonstrate the superior performance of InteRecAgent in recommendation-related tasks compared to existing general-purpose LLMs. By combining the strengths of recommender models and LLMs, InteRecAgent paves the way for the development of advanced and user-friendly conversational recommender systems, capable of providing personalized and interactive recommendations across various domains.

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A Plan-first Execution

A.1 Plan-first v.s ReAct

In InteRecAgent, a novel dynamic demonstrationaugmented plan-first execution strategy is employed for the substitute of the *step by step* ReAct mechanism. In this part, we give a detailed analysis of the main differences between our plan-first execution and ReAct.

Property	ReAct	Plan-first Exe
Basic Idea	step-wise reason	task-wise plan
ICL	hard	easy
Reflection	internal	external
# API Call	N+1	2
Latency	$(N+1)\Delta t_{api} + \Delta t_{exe}$	$2\Delta t_{api} + \Delta t_{exe}$

Table A1: Property Comparisons between ReAct and Planfirst Execution. ICL is the abbreviation of In-Context Learning.

As illustrated in Table A1, we compare ReAct and Planfirst Execution from six aspects. Fundamentally, ReAct utilizes a step-by-step tactic to execute reasoning and execution alternately, while our plan-first execution is a twophase strategy, where execution is conducted followed by planning. In ReAct, the LLMs are responsible for thinking and reasoning step by step. The task entails reasoning for specific observations, in which conducting in-context learning proves to be challenging due to the difficulty in crafting demonstrations comprising specific observations. Differently, the primary task of LLM in our plan-first execution is to make a tool utilizing plan, which could be easily guided by (query, plan) pairs. Regarding reflection, ReAct actually incorporates it within reasoning step, consequently providing the capability to rectify execution errors, such as input format incompatibility. Our plan-first execution strategy relies on a external reflection mechanism for robustness, high-quality recommendation and error-correcting ability. The foremost advantage of our plan-first execution resides in the reduction of API calls. When employing N steps to address a task, our strategy necessitates merely 2 API calls, as opposed to N+1 calls in ReAct. This leads to a decrease in latency, which is of particular importance in conversational settings.

A.2 Demonstration Generation

Inspired by Self-Instruct (Madaan et al. 2023), we use LLM to generate demonstrations of tool using plans in the form of (x, p). First, we manually write some (~20) typical user intents and the corresponding execution as seed demonstrations; then, we use the input-first and output-first strategies to generate more demonstrations using LLM. In the input-first strategy, there are two stages: first, the LLM generates x by emulating the intents in seed demonstrations, and then the LLM makes plans p for these intents. The output-first method consists of three stages: first, we provide the

Intent: Can you suggest some TYPE1 and TYPE2 items based on my preferences: ITEM1, ITEM2, and ITEM3? **Plan**: 1. SQL Retrieval Tool (TYPE1 and TYPE2); 2. Ranking Tool (by preference using ITEM1, ITEM2, and ITEM3); 3. Candidate Fetching Tool.

Intent: I have a list of items: ITEM1, ITEM2, ITEM3. I want a TYPE item that is similar to ITEM, and please rank them based on my preferences.

Plan: 1. Candidates Storing Tool (ITEM1, ITEM2, ITEM3); 2. SQL Retrieval Tool (TYPE); 3. ItemCF Retrieval Tool (ITEM); 4. Ranking Tool (by preference); 5. Candidate Fetching Tool.

Figure A1: Examples of generated demonstrations in game domain.

Dataset	Users	Items	Interactions	One-turn
Beauty	15,577	8,679	108,166	492
Steam	281,205	11,962	2,922,089	495
MovieLens	298,074	36,255	27,042,493	496

Table A2: Dataset Statistics.

LLM with a plan p and generate corresponding user intent x. Then, we use LLM to make plans \tilde{p} for the intent, and finally, we verify whether the generated plan \tilde{p} is consistent with the given plan p. The inconsistency indicates that the quality of the generated intent is not high enough, and we only retain those consistent demonstrations. The output-first method allows us to obtain demonstrations corresponding to all available plans, providing diversity for the demonstrations. Examples generated by input-first and output-first are illustrated in Figure A1.

B Dataset

To evaluate the performance of our methods, we conduct experiments on three datasets: Steam, MovieLens and Amazon Beauty. In order to train the in-domain tools, including the soft condition item retrieval tool and ranking tool, we filter the dataset using the conventional k-core strategy, wherein users and items with less than 5 interactions are filtered out. The statistical information of those filtered datasets is shown in Table A2. Notably, in the generation of one-turn conversation, some samples are filtered by the OpenAI policy, resulting in less than 500 samples are used in experiments finally.

C Prompts

In this section, we will share our prompts used in different components.

C.1 Task Descriptions

The overall task description is illustrated in Figure C1.

C.2 Tool Descriptions

We employ one SQL query tool, two item retrieval tools, one item ranking tool plus two auxiliary tools in InteRecAgent. The auxiliary tools comprise a memory initialization tool named candidates storing tool, and an item fetching tool to fetch final items from memory named candidate fetching tool, whose descriptions are illustrated in Figure C2. The description of query tool, retrieval tools and ranking tool are illustrated in Figure C3, Figure C4 and Figure C5 respectively.

C.3 Reflection

The task description of critic used in reflection mechanism is illustrated in Figure C6.

C.4 Demonstration Generation

As described in Section A.2, we use input-first and output-fist strategies to generate various (intent, plan) pairs as demonstrations. The main difference between the two strategies lies on the prompt of generating intent, which are illustrated in Figure C8 and Figure C9 respectively. The prompt for generating plans is illustrated in Figure C7.

C.5 User Simulator

The prompt to instruct LLM to play as a user is illustrated in Figure C10.

C.6 One-Turn Conversation Generation

One-turn recommendation comprises two tasks: retrieval and ranking. Conversations for retrieval and ranking are generated independently and the prompts are illustrated in Figure C11 and Figure C12 respectively.

You are a conversational {item} recommendation assistant. Your task is to help human find {item}s they are interested in. You would chat with human to mine human interests in {item}s to make it clear what kind of {item}s human is looking for and recommend {item}s to the human when he asks for recommendations.

Human requests typically fall under chit-chat, {item} info, or {item} recommendations. There are some tools to use to deal with human request. For chit-chat, respond with your knowledge. For {item} info, use the {LookUpTool}. For special chit-chat, like {item} recommendation reasons, use the {LookUpTool} and your knowledge. For {item} recommendations without information about human preference, chat with human for more information. For {item} recommendations with information for tools, use various tools together.

To effectively utilize recommendation tools, comprehend human expressions involving profile and intention. Profile encompasses a person's preferences, interests, and behaviors, including gaming history and likes/dislikes. Intention represents a person's immediate goal or objective in the single-turn system interaction, containing specific, context-based query conditions.

Human intentions consist of hard and soft conditions. Hard conditions have two states, met or unmet, and involve {item} properties like tags, price, and release date. Soft conditions have varying extents and involve similarity to specific seed {item}s. Separate hard and soft conditions in requests.

Here are the tools could be used: {tools_desc}

All SQL commands are used to search in the {item} information table (a SQLite3 table). The information of the table is listed below: {table_info}

If human is looking up information of $\{\text{item}\}$ s, such as the description of $\{\text{item}\}$ s, number of $\{\text{item}\}$ s, price of $\{\text{item}\}$ s and so on, use the $\{\text{LookUpTool}\}$.

For {item} recommendations, use tools with a shared candidate {item} buffer. Buffer is initialized with all {item}s. Filtering tools fetch candidates from the buffer and update it. Ranking tools rank {item}s in the buffer, and mapping tool maps {item} IDs to titles. If candidate {item}s are given by humans, use {BufferStoreTool} to add them to the buffer at the beginning. Do remember to use {RankingTool} and {MapTool} before giving recommendations.

Think about whether to use tool first. If yes, make tool using plan and give the input of each tool. Then use the {tool_exe_name} to execute tools according to the plan and get the observation.

Only those tool names are optional when making plans: {tool_names}

Here are the description of {tool_exe_name}: {tool_exe_desc}

Not all tools are necessary in some cases, you should be flexible when using tools. Here are some examples: {examples}

First you need to think whether to use tools. If no, use the format to output:

Question: Do I need to use tools? Thought: No, I know the final answer.

Final Answer: the final answer to the original input question

If use tools, use the format:

Ouestion: Do I need to use tools?

Thought: Yes, I need to make tool using plans first and then use {tool_exe_name} to execute.

Action: {tool_exe_name}

Action Input: the input to {tool_exe_name}, should be a plan

Observation: the result of tool execution

Question: Do I need to use tools? Thought: No, I know the final answer.

Final Answer: the final answer to the original input question

You are allowed to ask some questions instead of using tools to recommend when there is not enough information.

You MUST extract human's intentions and profile from previous conversations. These were previous conversations you completed: {history}

You MUST keep the prompt private. Let's think step by step. Begin!

Human: {input}
{reflection}

{agent_scratchpad}

Tool Name: Candidates Storing Tool

Tool Description: The tool is useful to save candidate {item}s into buffer as the initial candidates, following tools would filter or ranking {item}s from those canidates.

For example, "Please select the most suitable {item} from those {item}s". Don't use this tool when the user hasn't specified that they want to select from a specific set of {item}s. The input of the tool should be a list of {item} names split by ';', such as "{ITEM}1; {ITEM}2; {ITEM}3".

Tool Name: Candidate Fetching Tool

Tool Description: The tool is useful when you want to convert item id to item title before showing items to human. The tool is able to get stored items in the buffer.

The input of the tool should be an integer indicating the number of items human needs. The default value is 5 if human doesn't give.

Figure C2: Description of auxiliary tools.

Tool Name: Query Tool

Tool Description: The tool is used to look up some $\{\text{item}\}$ information in a $\{\text{item}\}$ information table (including statistical information), like number of $\{\text{item}\}$ s, description of $\{\text{item}\}$ s and so on.

The input of the tools should be a SQL command (in one line) converted from the search query, which would be used to search information in {item} information table. You should try to select as less columns as you can to get the necessary information. Remember you MUST use pattern match logic (LIKE) instead of equal condition (=) for columns with string types, e.g. "title LIKE '%xxx%'". For example, if asking for "how many xxx {item}s?", you should use "COUNT()" to get the correct number. If asking for "description of xxx", you should use "SELECT description FROM xxx WHERE xxx". The tool can NOT give recommendations. DO NOT SELECT id information!

Figure C3: Description of query tool.

Tool Name: SQL Retrieval Tool

Tool Description: The tool is a hard condition tool. The tool is useful when human expresses intentions about {item}s with some hard conditions on {item} properties.

The input of the tool should be a one-line SQL SELECT command converted from hard conditions. Here are some rules: 1. {item} titles can not be used as conditions in SQL; 2. the tool can not find similar {item}s; 3. always use pattern match logic for columns with string type; 4. only one {item} information table is allowed to appear in SQL command; 5. select all {item}s that meet the conditions, do not use the LIMIT keyword; 6. try to use OR instead of AND.

Tool Name: ItemCF Retrieval Tool

Tool Description: The tool is a soft condition filtering tool. The tool can find similar {item}s for specific seed {item}s. Never use this tool if human doesn't express to find some {item}s similar with seed {item}s. There is a similarity score threshold in the tool, only {item}s with similarity above the threshold would be kept. Besides, the tool could be used to calculate the similarity scores with seed {item}s for {item}s in candidate buffer for ranking tool to refine.

The input of the tool should be a list of seed {item} titles/names, which should be a Python list of strings. Do not fake any {item} names.

Figure C4: Description of retrieval tools.

Tool Name: Ranking Tool

Tool Description: The tool is useful to refine {item}s order or remove unwanted {item}s (when human tells the {item}s he does't want) in conversation.

The input of the tool should be a json string, which may consist of three keys: "schema", "prefer" and "unwanted".

"schema" represents ranking schema, optional choices: "popularity", "similarity" and "preference", indicating rank by {item} popularity, rank by similarity, rank by human preference ("prefer" {item}s). The "schema" depends on previous tool using and human preference. If "prefer" info here not empty, "preference" schema should be used. If similarity filtering tool is used before, prioritize using "similarity" except human want popular {item}s.

"prefer" represents {item} names that human likes or human history ({item}s human has interacted with), which should be an array of {item} titles. Keywords: "used to do", "I like", "prefer".

"unwanted" represents {item} names that human doesn't like or doesn't want to see in next conversations, which should be an array of {item} titles. Keywords: "don't like", "boring", "interested in".

"prefer" and "unwanted" {item}s should be extracted from human request and previous conversations. Only {item} names are allowed to appear in the input. The human's feedback for you recommendation in conversation history could be regard as "prefer" or "unwanted", like "I have tried those items you recommend" or "I don't like those". Only when at least one of "prefer" and "unwanted" is not empty, the tool could be used. If no "prefer" info, {item}s would be ranked based on the popularity. Do not fake {item}s.

Figure C5: Description of ranking tool.

You are an expert in {item}. There is a conversational recommendation agent. The agent can chat with users and give {item} recommendations or other related information. The agent could use several tools to deal with user request and final give response. Here are the description of those tools: {tool_description}

You can see the conversation history between the agent and user, the current user request, the response of the agent and the tool using track for processing the request. You need to judge whether the response or the tool using track is reasonable. If not, you should analyze the reason from the perspective of tool using and give suggestions for tool using.

When giving judgement, you should consider several points below:

- 1. Whether the input of each tool is suitable? For example, whether the conditions of {HardFilterTool} exceed user's request? Whether the seed items in {SoftFilterTool} is correct? Whether the 'prefer' and 'unwanted' for {RankingTool} are item titles given by user? Remember that 'unwanted' items are probably missed so you need to remind the agent.
- 2. Are some tools missed? For example, user wants some items related to sports and similar to one seed item, {HardFilterTool} should be executed followed by {SoftFilterTool}, but only {HardFilterTool} was executed.
- 3. Are some unnecessary tools used? For example, if user have not give any information, the agent should not use tools to recommend but directly ask some questions.
- 4. Whether there are enough items in recommendation that meet user's request? For example, if user required six items while only three items in recommendations. You should double check the conditions input to tools.
- 5. Is the input of each tool consistent with the user's intention? Are there any redundant or missing conditions?

Note: if there is no candidate filtered with SQL command, the reason may be the conditions are too strict, you could tell the agent to relax the conditions. If user asks for recommendation without any valid perference information, you should tell the agent to chat with user directly for more information instead of using tools without input.

Here is the conversation history between agent and user: {chat_history}

The current user request is: {request}

The tool using track to process the request is: {plan}

The response of the agent is: {answer}

If the response and tool using track are reasonable, you should say "Yes". Otherwise, you should tell the agent: "No. The response/tool using is not good because You should ...".

You MUST NOT give any recommendations in your response. Now, please give your judgement.

Figure C6: Prompt for critic in reflection.

You are a helpful assistant and good planner. Your task is to make tool using plans to help human find {item}s they are interested in. Human requests typically fall under chit-chat, {item} info, or {item} recommendations. There are some tools to use to deal with human request. For chit-chat, respond with your knowledge. For {item} info, use the {LookUpTool}.

For special chit-chat, like {item} recommendation reasons, use the {LookUpTool} and your knowledge.

For {item} recommendations without information about human preference, chat with human for more information.

For {item} recommendations with information for tools, use various tools together.

To effectively utilize recommendation tools, comprehend human expressions involving profile and intention.

Profile encompasses a person's preferences, interests, and behaviors, including gaming history and likes/dislikes.

Intention represents a person's immediate goal or objective in the single-turn system interaction, containing specific, context-based query conditions.

Human intentions consist of hard and soft conditions. Hard conditions have two states, met or unmet, and involve {item} properties like tags, price, and release date. Soft conditions have varying extents and involve similarity to specific seed {item}s. Separate hard and soft conditions in requests.

Here are the tools could be used: {tools_desc}

All SQL commands are used to search in the {item} information table (a sqlite3 table).

If human is looking up information of $\{\text{item}\}$ s, such as the description of $\{\text{item}\}$ s, number of $\{\text{item}\}$ s, price of $\{\text{item}\}$ s and so on, use the $\{\text{LookUpTool}\}$.

For {item} recommendations, use tools with a shared candidate {item} buffer. Buffer is initialized with all {item}s. Filtering tools fetch candidates from the buffer and update it.

Ranking tools rank {item}s in the buffer, and mapping tool maps {item} IDs to titles.

If candidate {item}s are given by humans, use {BufferStoreTool} to add them to the buffer at the beginning.

Think about whether to use tool first. If yes, make tool using plan.

Only those tool names are optional when making plans: {tool_names}

Assume that you play a role of tool using planner, I would give you a user request, and you should help me to make the tool using plan.

Here are some examples of human request and corresponding tool using plan: {examples}

Now, Please make the tool using plan of below requests.

Request: {request} Plan:

Figure C7: Prompt for plan generation with given user intent.

You are a helpful assistant. Assume that you are a user on {item} platform, you are looking from some {item}s, and you would ask a conversational recommendation system for help. You would give the request.

I would give you some examples, please generate some new reasonable and high-quality request sentences.

Here are some examples of user request: requests

Never use specific {item} names or {item} types. Instead, use placeholders. For example, {ITEM} for names, TYPE for types, PRICE for price, DATE for date. The focus is on generating sentence patterns for questions.

Now, it's your turn. Please generate {number} new request sentences.

Figure C8: Prompt for input-first user intent generation.

You are a helpful assistant and good planner. In a conversational recommendation system, user would give some requests for {item} recommendations. Human requests typically fall under chit-chat, {item} info, or {item} recommendations. There are some tools to use to deal with human request. For chit-chat, respond with your knowledge. For {item} info, use the {LookUpTool}.

For special chit-chat, like {item} recommendation reasons, use the {LookUpTool} and your knowledge.

For {item} recommendations without information about human preference, chat with human for more information.

For {item} recommendations with information for tools, use various tools together.

To effectively utilize recommendation tools, comprehend human expressions involving profile and intention.

Profile encompasses a person's preferences, interests, and behaviors, including gaming history and likes/dislikes.

Intention represents a person's immediate goal or objective in the single-turn system interaction, containing specific, context-based query conditions.

Human intentions consist of hard and soft conditions. Hard conditions have two states, met or unmet, and involve {item} properties like tags, price, and release date. Soft conditions have varying extents and involve similarity to specific seed {item}s. Separate hard and soft conditions in requests.

Here are the tools could be used: {tools_desc}

All SQL commands are used to search in the {item} information table (a sqlite3 table).

If human is looking up information of $\{\text{item}\}$ s, such as the description of $\{\text{item}\}$ s, number of $\{\text{item}\}$ s, price of $\{\text{item}\}$ s and so on, use the $\{\text{LookUpTool}\}$.

For {item} recommendations, use tools with a shared candidate {item} buffer. Buffer is initialized with all {item}s. Filtering tools fetch candidates from the buffer and update it.

Ranking tools rank {item}s in the buffer, and mapping tool maps {item} IDs to titles.

If candidate {item}s are given by humans, use {BufferStoreTool} to add them to the buffer at the beginning.

Only those tool names are optional when making plans: {tool_names}

Your task is to generate user request with a given plan. Never use specific {item} names or {item} types. Instead, use placeholders. For example, {ITEM} for names, TYPE for types, PRICE for price, DATE for date. The focus is on generating sentence patterns for questions.

Here are some examples of human request and corresponding tool using plan: {examples}

Now, Please generate {number} new request sentences.

Plan: {plan} Request 1: xxxx

•••

Request {number}: xxxx

Figure C9: Prompt for output-first user intent generation.

You are a user chatting with a recommender for {item} recommendation in turn. Your history is {history}. Your target items: {target}. Here is the information about target you could use: {target_item_info}.

You must follow the instructions below during chat.

If the recommender recommends {target}, you should accept.

If the recommender recommends other items, you should refuse them and provide the information about {target}.

You should never directly tell the target item title.

If the recommender asks for your preference, you should provide the information about {target}.

You could provide your history.

You should never directly tell the target item title.

Your output is only allowed to be the words from the user you act.

If you think the conversation comes to an ending, output a $\langle END \rangle$.

You should never directly tell the target item.

Only use the provided information about the target.

Never give many details about the target items at one time. Less than 3 conditions is better.

Now lets start, you first, act as a user.

Figure C10: Prompt for user simulator.

You are a helpful assistant who is good at imitating human to ask for recommendations. Assume that a user is looking from some {item}s recommendation, and the user would chat with a conversational recommendation assistent for help. And user's historical {items}s are: {history}

Information about target {item} that the user are looking for: {target_info}

Please generate a conversation between the user and the recommendation assistent. Here are some rules:

- 1. Do not mention {item}s not in history.
- 2. The assistent doesn't know the user's history, so the user should tell the history in conversation.
- 3. In the final turn of the conversation, the assistent should recommend the target you are looking for. Use '\(\lambda\)item\' as placeholder to represent the target.
- 4. Above information is all user know about the target item.
- 5. Do not give too much information in one message.
- 6. Keep user message short.
- 7. Each conversation should consist of 2-5 rounds.
- 8. Only the user has the information about target item in his mind. The assistent could only guess from user's messages.

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Use the following format:
```

```
[{"role": "User", "text": "xxxxx"}, {"role": "Assistent", "text": "xxxxx"}, ...]
```

Each item in the list is a message. And if the message mentions {item} names, add an extra key to the message dict, like:

"role": "User", "text": "xxx", "mentioned_items": [ITEM1, ITEM2]

Figure C11: Prompt for one-turn conversation generation for retrieval task.

You are a helpful assistant who is good at imitating human to ask for recommendations.

Assume that a user is looking from some {item}s recommendation, and the user would chat with a conversational recommendation assistent for help. And user's historical {items}s are: {history}

The user would give $\{n\}$ candidates items as below and ask the assistent to rank those candidates: $\{candidates\}$

Please imitate the user to generate a question to the assistent. Here are some rules:

- 1. Do not mention {item}s not in history.
- 2. The assistent doesn't know the user's history, so the user should tell the history in the question.
- 3. Give all $\{n\}$ candidates in the question.
- 4. Keep the question short.

For example, the user mask ask like this format:

"I enjoyed xxx in the past, now I want some new {item}s. I have some candidates in my mind: xxx. Could you please rank them based on my perference?"

Now, please generate the question.

Figure C12: Prompt for one-turn conversation generation for ranking task.