When Large Language Model based Agent Meets User Behavior Analysis: A Novel User Simulation Paradigm

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Abstract

User behavior analysis is crucial in human-centered AI applications. In this field, the collection of sufficient and high-quality user behavior data has always been a fundamental yet challenging problem. An intuitive idea to address this problem is automatically simulating the user behaviors. However, due to the subjective and complex nature of human cognitive processes, reliably simulating the user behavior is difficult. Recently, large language models (LLM) have obtained remarkable successes, showing great potential to achieve human-like intelligence. We argue that these models present significant opportunities for reliable user simulation, and have the potential to revolutionize traditional study paradigms in user behavior analysis. In this paper, we take recommender system as an example to explore the potential of using LLM for user simulation. Specifically, we regard each user as an LLM-based autonomous agent, and let different agents freely communicate, behave and evolve in a virtual simulator called **RecAgent**. For comprehensively simulation, we not only consider the behaviors within the recommender system (e.g., item browsing and clicking), but also accounts for external influential factors, such as, friend chatting and social advertisement. Our simulator contains at most 1000 agents, and each agent is composed of a profiling module, a memory module and an action module, enabling it to behave consistently, reasonably and reliably. In addition, to more flexibly operate our simulator, we also design two global functions including real-human playing and system intervention. To evaluate the effectiveness of our simulator, we conduct extensive experiments from both agent and system perspectives. In order to advance this direction, we have released our project at https://github.com/RUC-GSAI/YuLan-Rec.

1 Introduction

"Earth is a machine-like simulation that depends on humans creating emotions with their Shadow Bodies in order to suck divine love into this simulated reality."

Deborah Bravandt

Human-centered artificial intelligence (AI) strives to advance the techniques that serve humanity, garnering substantial attention from both industry and academic communities over the past few decades. User behavior analysis plays a crucial role in human-centered AI, dedicated to understanding and deducing human preferences and behavioral patterns [26]. The accuracy of user behavior analysis relies on the availability of adequate and high-quality data. However, acquiring such data in real-world applications is prohibitively expensive or even pose ethical dilemmas (*e.g.*, collecting privacy information). An intuitive idea to solve this problem could be automatically simulating the user

behaviors. However, this method is challenging because it requires reliable simulation of complex human cognitive mechanisms, which is hard for traditional machine learning models.

Recently, large language models (LLM) [49] have demonstrated immense potential in achieving human-level intelligence through learning extensive web data. They can offer significant opportunities to simulate subjective aspects in the analysis of user behavior. Inspired by such opportunities, we propose a novel direction, that is, LLM-based user simulation, to advance simulation based studies and explore more diverse research paradigms in the field of user behavior analysis. While this direction seems to be possible, effectively transferring the capability of LLMs for simulating user behaviors is not straightforward. To begin with, the users in real-world scenarios may have diverse preferences, personalities and backgrounds, how to enable LLMs to effectively simulate different user characters is not easy. Then, the user behaviors in practice are dynamically connected, that is, the previous behaviors may influence the subsequent ones. However, ordinary LLMs are usually good at accomplishing one-shot static tasks, which requires us to design additional modules to enhance their capability for handling dynamic problems. In addition, in real-world scenarios, there are a large amount of user behaviors. However, many of them are trivial, for instance, when studying user behaviors on the Internet, activities such as "eating breakfast" and "brushing teeth" are not significant. Thus, it is impossible and not necessary to simulate all the user behaviors. Which user behaviors should be simulated need our careful designs. Beyond the above challenges from the user perspective, how to design the simulator system to effectively organize different users, especially tailored for LLMs has not been investigated before, and need our significant efforts.

To solve the above problems, we take recommender system as an example, and propose a novel LLM-based recommender simulator called **RecAgent**. From the user perspective, we simulate each user by an LLM-based autonomous agent, which is composed of a profiling module, a memory module and an action module. The profiling module can flexibly and efficiently generate different agent profiles. The memory module is designed to make user behaviors more consistent in dynamic environments, where the previous behaviors of the users can be stored in memory to influence their subsequent decisions. In the action module, we incorporate not only the user behaviors within the recommender system, such as item clicking and browsing, but also consider external factors like friend chatting and social advertisement to more comprehensively simulate the user decision process. By incorporating all these modules, we aim to achieve more consistent, reasonable, and reliable user behaviors simulation. From the system perspective, our simulator consist of a maximum of 1000 agents. It is executed in a round-by-round manner. In each round, the agents autonomously perform actions based on their predefined activity levels. To facilitate human-agent collaboration, we allow a real human to play as an agent in the simulator, and interact with the recommender system and the other agents. Additionally, one can also actively intervene the system by pausing the simulation process, modifying agent profiles, and then re-running the simulator. Such intervention can be benefit for studying the effects of emergency events, user counterfactual behaviors and so on.

To evaluate the effectiveness of our simulator, we conduct extensive experiments from both agent and system perspectives. From the agent perspective, we mainly evaluate (1) whether different types of memories can produce reasonable results, and (2) whether the agent can invoke informative and relevant memories to take actions in different scenarios. From the system perspective, we focus on (1) whether the simulated user behaviors are sufficiently reliable, as compared with traditional simulation methods and real-human labeled results, (2) the efficiency of our simulator, and (3) whether actively intervening the simulator can result in expected user behaviors. In summary, the main contributions of this paper are as follows:

- We propose a novel direction in the field of user behavior analysis, that is, leveraging LLMs to simulate user behaviors via building autonomous agents.
- As the first step towards the above direction, we take recommender system as an example, and design an LLM-based simulator called RecAgent.
- To effectively simulate user behaviors, we propose an effective agent framework including a profiling module, a memory module and an action module. In addition, we also design system functions including real-human playing and global intervention to flexibly operate the simulator.
- We conduct extensive experiments to study the effectiveness and efficiency of our simulator from both agent and system perspectives.

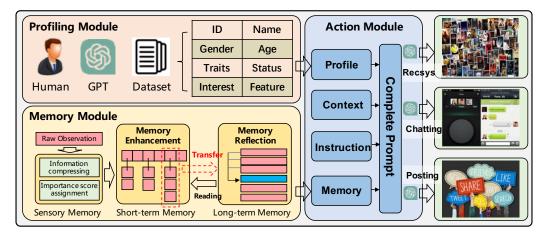


Figure 1: The framework of a single agent, which is composed of a profiling module, a memory module and an action module. The profiling module and memory module jointly influence the action module, which produces different types of user behaviors.

In the following, we first detail our simulator, RecAgent, where we sequentially introduce the agent framework to ensure reliable user behavior simulation and the system environment to effectively organize different agents. Then, we discuss the related work of this paper. The experiments to evaluate our simulator comes in the next. At last, we present the limitations of our simulator, conclude this work, and present future directions.

2 RecAgent

In this section, we first build an agent framework by empowering LLMs with necessary capabilities for user behavior simulation. Then, we detail the system environment, including the simulation protocol, recommendation algorithm, real-human playing and system intervention.

2.1 The Agent Framework

As mentioned before, while LLMs have displayed unprecedented potential in attaining human-like intelligence, many challenges still exist on leveraging them to simulate real user behaviors. To solve these challenges, we design an agent framework, including a profiling module, a memory module, and an action module to enhance ordinary LLMs. The overall architecture of the framework can be seen in Figure 1. The profile module is responsible for assigning the agents with different characters. The memory module is designed to assist the simulation of user behavior dynamics. The action module determines the simulated user behaviors, such as item click, browsing, friend chatting. In the following, we detail these modules.

2.1.1 Profiling Module

User profile is an important concept in the recommendation domain, which determines the user preferences, personalities and behavior patterns. In our simulator, the user profiles include ID, name, gender, age, traits, career, interests, and behavioral features. The traits describe the user's personality, such as being "compassionate", "ambitious", or "optimistic". The interests indicate the user's preferences on the items, such as "sci-fi movies" or "comedy videos". To more accurately describe users in the recommendation domain, we use ChatGPT to conclude five types of notable behavior features of online users, and incorporate them into the user profiles. These features include: (1) **Watcher**: the users with this feature will actively provide feedback and ratings to the interacted items. (2) **Explorer**: the users with this feature will actively search for items they have heard before, and produce detailed experiences. (3) **Critic**: the users with this feature demands high standards for items, and may criticize both the recommendation system and the items. (4) **Chatter**: the users with this feature will always engage in private conversations, and trust friends' recommendations. (5) **Poster**: the users with this feature enjoy publicly posting on social media and sharing content

ID	Name	Gender	Age	Traits	Career	Interest	Feature
0	David Smith	male	25	compassionate, caring, ambiti ous, optimistic	photographer	sci-fi movies, comedy movies	Watcher;Critic;Poster
1	David Miller	female	39	Funloving, creative, practical, energetic, patient	writer	action movies, scifi movies, classic movies	Watcher;Explorer;Poster
2	James Brown	male	70	independent, creative, patient , empathetic	engineer	comedy movies, familyfriendly movi es, documentaries, thriller movies	Watcher;Critic;Poster
3	Sarah Miller	female	33	independent, compassionate	farmer	romantic movies, comedy movies, c lassic movies, family-friendly movies	Watcher;Critic;Poster
4	John Taylor	male	68	optimistic	doctor	action movies, thriller movies	Watcher;Poster
5	Sarah Williams	female	51	meticulous	musician	action movies, documentaries, scifi movies, familyfriendly movies	Watcher;Explorer;Chatter
6	James Jones	male	59	practical, funloving, creative, ambitious, caring	farmer	documentaries	Watcher;Poster
7	Jane Brown	female	30	patient, adventurous, fun- loving, optimistic	doctor	documentaries	Watcher;Explorer;Poster
8	David Jones	male	23	analytical, energetic, introspe ctive, independent	scientist	familyfriendly movies, thriller movie s, action movies, sci-fi movies	Poster
9	James Brown	female	20	ambitious, analytical, optimist ic, energetic, meticulous	designer	familyfriendly movies, romantic movies	Critic; Chatter
10	James Garcia	male	20	practical, energetic, introspect ive, patient	engineer	documentaries, thriller movies, com edy movies, classic movies, romanti c movie	Watcher; Explorer; Poster

Figure 2: Examples of the complete user profiles.

and insights with his friends. We present several examples of the complete user profiles in Figure 2. It should be noted that one can also set part of the user profiles as empty according to specific applications. In order to flexibly and efficiently generate the user profiles for the agents, we design the following three profile generation strategies:

- Handcrafting method: This method manually indicates the profile of each agent. For example, one can describe an agent by "David Smith, a 25-year-old male photographer". This method is very flexible, and people can easily simulate different types of users.
- **GPT-based method**: This method generates the profile information based on GPT. People only have to design appropriate prompts, such as "Here is the user's profile table. Please refer to the existing information and continue to complete the user profile.", and then request GPT to generate more agent profiles. This method is highly efficient, significantly reducing the time cost for agent profile generation.
- **Real-data alignment method**: This method leverages user backgrounds in real-world datasets to profile the agents. For example, one can leverage the previously interacted items of the users in the dataset as the agent profiles. This method can incorporate real-world knowledge into the simulation process, for example, the real distribution of user genders.

The above three methods are not isolate; rather, they can be combined to take the advantages of each method. For instance, one can indicate part of the user profiles manually to accurately control the user characters, and assign the remaining user profiles automatically using GPT to enhance the efficiency.

2.1.2 Memory Module

Recent advancements in cognitive neuroscience [5] highlight three key parts of human memory: sensory memory, short-term memory, and long-term memory. Sensory memory is responsible for processing the information perceived by humans directly from the environment. The information stored in this memory only last for a few hundred milliseconds. During this time, significant information is transferred to the short-term memory, while less important information is discarded. Short-term memory processes the information output from the sensory memory. The information here can be enhanced if the human repeatedly experiences similar events. After being enhanced several times, short-term memories can be converted into long-term memories. Long-term memory has the largest capacity and can store information for a long time. When humans takes action, relevant long-term memories are extracted to assist their decisions. In addition, human may also autonomously produce high-level insights from long-term memories. To reliably simulate user behaviors, we follow the above human memory mechanism to design the memory module of RecAgent. In the following, we first detail the agent sensory memory, short-term memory and long-term memory in RecAgent, and then introduce how they work together to accomplish different memory operations.

Sensory memory. In the simulation process, we define an observation as an event experienced by the agent, for example, an observation can be "David Miller enters recommendation system" or "David Smith watches a movie called Fast & Furious". The observation is described and recorded directly using natural language, which can retain rich semantic information and is understandable to humans. All the observations are firstly input into the sensory memory, which are then processed by two sequential steps. In the first step, the observations are compressed into more informative and concise sentences based on LLMs. This step can remove noisy and unimportant contents, which may mislead the agent behaviors. In addition, the compressed memory can save much space to improve the operation efficiency. We present an example of this step in the Appendix.

In the second step, we assign each compressed observation with a score to indicate its importance. In specific, we consider item-related information to be more important. For example, "feelings, chatting and posting messages on items" are more important observations than the action of "entering recommendation system". The importance score is leveraged in the memory reading process, and more important memories are more likely to be recalled. In addition, each observation is also accompanied with its timestamp. Finally, the output from the sensory memory is a triplet M=< c, s, t>, where c is the content of the compressed observation, s and t are the corresponding importance score and timestamp, respectively.

Short-term memory. Short-term memory serves as an intermediate module connecting sensory memory to long-term memory. This module determines which information should be transformed into long-term memory, and how to transform this information. Similar to the human memory mechanism, in our simulator, if an agent repeatedly encounters similar observations, then the related short-term memories are enhanced and transformed into long-term memories. Formally, suppose existing short-term memory is MEM = $\{M_1, M_2, ..., M_n\}$, where $M_i = \langle c_i, s_i, t_i \rangle$ is a record output from the sensory memory. For a new record $M_{n+1} = \langle c_{n+1}, s_{n+1}, t_{n+1} \rangle$, we first compute the similarity between c_{n+1} and each c_i in MEM based on their embeddings. If the similarity is higher than a predefined threshold, we add M_{n+1} into M, and label that M_i has been enhanced by M_{n+1} . If all the similarities are lower than the threshold, M_{n+1} is added into M without enhancing any record. After a memory record has been enhanced K times, it is then transformed into long-term memories. More specifically, we first summarize the record and the ones used to enhance it into high-level insights, and then transform both the record and the insights into long-term memories. The record itself is specific, while the insights are more general. By incorporating both of them, we hope that the agent can acquire specific knowledge without compromising its ability to generalize. We present an example on the insight generation process in the Appendix.

Long-term memory. Long-term memory stores important information that can be reused in similar environments or generalize to unseen observations, which enables the agents to behave more consistently and reasonably. The capacity of the long-term memory is larger than the other two types of memories. Each memory record can be forgotten according to a predefined probability associated with the importance score and timestamp. Intuitively, if the memories are recent and important, then they have lower forgetting probabilities. In specific, according to cognitive neuroscience [46, 4], the forgetting rate of human memory is fast in the beginning, and then gradually slows down over time. Therefore, in our simulator, for a memory M_i , it is forgotten with a probability that is proportional to the following power function:

$$g(M_i) = 1 - \frac{s_i + r_i}{2} * \max(r_i^{\beta}, \delta),$$

where s_i and r_i are normalized recency and importance scores in (0.0, 1.0), larger values indicate that the memory is more recent and important. By $\max(r_i^\beta, \delta)$, we would like to make important memories produced long time ago can still be recalled. $\delta \in (0.0, 1.0)$ is a strength parameter determining when to consider the power function of r_i^β . Extremely, if $\delta \to 1.0$, the power function is inactivated, and $g(M_i)$ is only determined by the average between the recency and importance scores. $\beta > 1.0$ is a hyper-parameter controlling the power function shape. For more intuitively understanding this function, we present its curves with different hyper-parameters in the Appendix.

Based on the collaboration between the above three types of memories, the agents can accomplish the following memory operations to support their behaviors.

Memory writing. In this operation, the raw observations are firstly input into the sensory memory to remove irrelevant and unimportant information. Then, the processed observations are stored

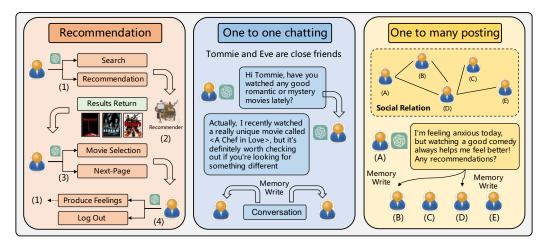


Figure 3: Illustration of the simulated behaviors. In the **recommendation behaviors**, an agent first decide whether she would like to actively search a movie or receive recommendations from the website. Then the website returns the search/recommendation results. The agent can select several movies from the results, or ask for more results. Once the agent have watched the movies, it will produce many feelings, which are stored into her memory. In the **chatting behaviors**, two agents talk about a movie. After the chat, their conversation is written into their memories. In the **posting behaviors**, an agent post a message on the social media. This message is received by all its friends, and written into their memories.

in short-term memory, which can be enhanced by similar observations. If an observation can be enhanced K times, it is then written into long-term memory.

Memory reading. In this operation, the agent extracts information from the memories that are relevant to the current observation. The extracted memories consist of two parts. The first part is extracted from the long-term memory, using the current observation as a query to retrieve the top-N memory records. The second part includes all the short-term memory. The strategy of combining long-term and short-term memories can simultaneously capture user general and recent preferences, which has been widely adopted in the recommendation domain [20, 44].

Memory reflection. In this operation, the agent can generate high-level ideas based on specific observations. This operation only happens in long-term memory. We follow [28] to implement this operation, but a significant difference is that we merge the memories and insights which are highly similar to save the memory space and remove redundant information.

2.1.3 Action Module

In our simulator, the action module is responsible for producing specific user behaviors, for example, "selecting a movie to watch", "chatting with a friend" or "posting a message on the social media". There are two significant problems for building the action module. To begin with, since our simulator is specially designed for the recommendation domain, it is unnecessary to simulate all the user behaviors. For example, behaviors like brushing teeth and eating breakfast are not crucial for addressing recommendation problems, and thus can be ignored. At the same time, limiting the behavior space can also help to build our simulator in a more feasible, controlled and focused manner. Thus, "determining which user behaviors to simulate?" is the first problem we need to address. Then, in the era of LLMs, prompt engineering is an effective strategy to influence LLM outcomes. As a result, "how to design proper prompts to enable the agent to behave reasonably?" is also an important problem. In the following, we illustrate our solutions to these problems more in detail.

Simulated behaviors. We argue that user behaviors in a recommender system are influenced by factors from two sources. The first one is inside the recommender system, for example, user decisions are often influenced by the recommended items, and user current behaviors can be impacted by the previous actions. The second source originates outside the recommender system. For instance, a user may choose to watch a movie based on a friend's recommendation, and advertisements may

encourage users to engage with specific items. Motivated by these analyses, we simulate the following user behaviors in our simulator (also can be seen in Figure 3):

• Behaviors inside the recommender system: (1) Searching behaviors: by these behaviors, the agents can actively search the items of interests. (2) Browsing behaviors: by these behaviors, the agents can receive recommendations from the system in a passive manner. (3) Clicking behaviors: by these behaviors, the agents can choose the items they would like to watch/purchase. (4) Next-page behaviors: these behaviors are triggered when the user is not satisfied with the current recommended/searched items, and would like to see more results.

The above behaviors may alternatively happen within a short time. For example, a user may first browse the recommended items, then find some items of interest, and search for more information about them. Finally, she clicks on one of the searched items.

• Behaviors outside the recommender system: Actually, there can be a large amount of external factors that may influence user behaviors in a recommender system. We believe social influence can be one of the most important factors, for example, real users always mutually influence each other and people can be easily affected by item advertisements. From different social behaviors, we abstract two general patterns: (1) One-to-one chatting, where two users discuss and exchange their information. This pattern includes user behaviors like chatting online via Twitter, WeChat and so on, or talking offline in a coffee shop. These behaviors may trigger users to interact with the discussed items, or change their memories to influence subsequent actions. (2) One-to-many posting, where one user shares information to the other users. This pattern includes user behaviors like posting opinions on social media, or sending business advertisements. These behaviors may influence the memories and actions of the users who receive the shared information.

Prompt Engineering Strategies. To effectively guide agent behaviors, we design a unified prompting framework as illustrated in Figure 1. There are four parts in the framework. The profile information aims to delineate the roles of the agent, encompassing characteristics like age, gender, personality, and others. For different behaviors, we employ ChatGPT to filter the complete profile information and retain the most relevant parts. The memory information comprises knowledge extracted from both short-term and long-term memories specific to the current behavior. The instruction describes the behavior requirements, for instance, if the current behavior is to produce feelings of a movie, then the instruction can be: "Imagine you are [agent-name], how will you feel about this movie just watched? Please share your personal feelings about the movie in one line". Additionally, one can enhance the agent capability of instruction following by incorporating several few-shot examples. The context reveals the states of the agent and the environment, such as the behavior timing. We present an example of the full prompt for producing feelings of a movie in Figure 4. More examples for the other behaviors are presented in the Appendix.

2.2 The System Environment

In the above section, we focus on introducing a single agent, illustrating its major components. In this section, we take a global perspective, and discuss four crucial aspects of the environment that the agents situated within, including the execution protocol, recommendation algorithm, real-human playing, and system intervention.

2.2.1 Round-based Execution

Our simulator operates in a round-by-round manner. During each round, the agents autonomously decide whether they would like to take actions. In real-world scenarios, different users may take actions (*e.g.*, accessing the recommender system or social media) with various activity levels. From a global perspective, these activity levels usually follow a long-tail distribution¹, meaning that a small number of individuals are highly active, while the majority of users have low action frequency. In order to incorporate such a characteristic into our simulator, we model the activity levels of different agents according to a Pareto distribution². In specific, the probability density of the activity level is represented as follows:

$$p(x) = \frac{\alpha x_{min}^{\alpha}}{x^{\alpha+1}},$$

¹https://en.wikipedia.org/wiki/Long_tail

²https://en.wikipedia.org/wiki/Pareto_distribution

Name: David Smith (age: 25), David Smith, a 25-year-old male photographer, is compassionate, caring, ambitious, and optimistic. He enjoys watching sci-fi and comedy movies and provides feedback and ratings to the recommendation system. He demands high standards for movies and the recommendation system and may criticize both. The observation about David watching "The Neon Bible" aligns with his interest in drama films and explores themes of faith, family, and coming-of-age. **Profile** It is August 18, 2023, 12:00 AM. Context Most recent observations: David Smith enjoys and finds captivating films that have captivating plots, humorous elements, thought-provoking themes, delve into complexities of human nature and sexual desire, uplift viewers, and have vibrant and engaging performances by the cast. Observation: David Smith has just finished watching Neon Bible, The (1995): "The Neon Bible" is a drama film set in the 1940s in a small southern town in the United States. It follows the story of a young boy named David who is struggling to understand the complexities of the world around him. David\'s mother is mentally unstable and his father is absent, leaving him to navigate the challenges of adolescence on his own. As he tries to make sense of his surroundings, he turns to religion and finds solace in the teachings of his local preacher. However, his faith is tested when he discovers the secrets and hypocrisies of those around him. The film explores themes of faith, family, and coming-of-age in a poignant and powerful way. Memory All occurrences of movie names should be enclosed with <>. David Smith has not seen this movie before. Imagine you are David Smith, how will you feel about this movie just watched? Please share your personal feelings about the movie in one line. Please act as David Smith well.

Figure 4: An example of the full prompt for producing feelings of a movie.

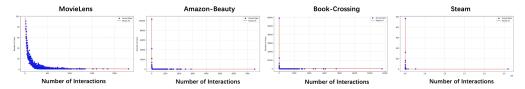


Figure 5: The results of using p(x) to fit real-world datasets. The blue points are the real-world data, and the red lines are the fitted distributions.

where x_{min} is the minimum activity level, and α is used to control the shape of the distribution.

To assess whether p(x) can be powerful enough to characterize real-world scenarios, we employ it to fit four well-known recommendation datasets including MovieLens, Amazon-Beauty, Book-Crossing, and Steam³, where we approximate the interaction numbers of the users as their activity levels. The results are illustrated in Figure 5. We can see, by varying the values of α , p(x) can effectively model the long-tail activity distribution of the real-world datasets.

2.2.2 Recommendation Algorithm

In our simulator, the recommendation algorithms are completely separated from the simulator, which facilitates flexible exploration of different problems. For instance, by implementing a random recommendation algorithm, researchers can generate uniform data that facilitates the study of unbiased recommendation. Furthermore, researchers can examine the effectiveness of different models by initiating two parallel simulators, and compare the user feedback or actively ask user feelings about the recommended items. Beyond manually implementing the recommendation algorithms, one can also easily incorporate external recommendation library (*e.g.*, RecBole⁴) into our simulator.

2.2.3 Role Playing

Beyond running our simulator in a complete virtual manner, we also allow real humans to involve into the simulation process. In specific, the real human can play as an agent, and interact with the recommender system or the other agents. This function actually introduces a novel execution fashion of our simulator, that is, running based on human-agent collaboration, which can help to improve the simulation effectiveness. For example, one can play as an agent, and actively correct the erroneous and hallucinatory behaviors of the other agents by chatting with them or posting

³https://github.com/RUCAIBox/RecSysDatasets

⁴https://recbole.io/

one-to-many messages, which can make the simulated behaviors more realistic and reliable. If we regard human behaviors as "complete real", and agent behaviors as "complete virtual", human-agent collaboration enables us to explore more intermediate states between these boundary cases. Human behaviors are more accurate, but costly. Agent behaviors are inexpensive, but could be erroneous and hallucinatory. Human-agent collaboration can help to achieve better trade-offs between the human and agent data, enabling the utilization of their respective advantages.

2.2.4 System Intervention

To flexibly control the simulation process, our simulator can be intervened from outside in a global manner. In specific, one can "interview" the agents by asking them questions like "What would you say when you want to discuss the movies you've recently watched with others?". Additionally, people can also pause the simulator at any point and modify certain factors (*e.g.*, user profiles) before resuming the simulation. This feature allows us to study many problems like the effects of emergency events or counterfactual user behaviors.

2.3 Discussion

Beyond the above detailed introduction on the motivation and construction of RecAgent, we further have the following discussions.

Relation with the previous work. RecAgent is inspired by a pioneer work called Generative Agent [28], where we share the same basic idea to leverage LLMs for human simulation. However, we focus on a specific task – the recommender system. This narrower scope simplifies the simulation process while enhancing its controllability and reliability. Recommender system has been extensively applied in numerous real-world applications, playing a pivotal role in modern business. Therefore, we believe that studying LLM-based recommendation simulation has significant impacts.

Extensibility of RecAgent. RecAgent is a highly extendable framework. From the agent perspective, the agent modules can be easily revised or deleted as they are completely decomposed, and changes to one module do not impact the others. In addition, one can also add more modules to implement more complex user behaviors. Here, a potential challenge lies in the prompting method. After revising the agent modules, it may be necessary to adjust the prompting strategy accordingly. From the simulator perspective, one can easily design additional user behaviors based on the paradigms employed for existing recommendation and social behaviors. As mentioned before, it is also flexible to incorporate more advanced recommender models and libraries.

Potential impacts of RecAgent. Real-data and simulation based studies are two common research paradigms in the recommendation domain. Real-data based studies can accurately learn the user real preferences and behavior patterns. However, this paradigm confronts two salient challenges. Firstly, this paradigm proves resource-intensive and lacks sustainability. This limitation restricts its utility to a narrow band of fixed problems, thereby impeding swift adaptation to burgeoning new problems in Web 2.0 (*e.g.*, RL-based recommendation and explainable recommendation [9, 42, 48, 2, 10]). Second, the richness of user interaction data in real-world contexts can be difficult to capture comprehensively. For instance, a user might choose to watch a film based on a friend's casual mention in conversation, an influencing factor that is difficult to capture through the lens of a recommender system. These hurdles significantly impact the trajectory of our in-depth investigation into recommender systems.

Simulation based studies can help explore a wider range of application scenarios. However, the majority of recommendation problems are highly subjective, and simulating the human mind can be challenging. Although there have been several promising user simulators, such as RecSim⁵ and VirtualTaobao⁶, they often simulate human minds using simple and naive functions, which may not be powerful enough to handle the complexity of the user decision-making mechanism.

RecAgent opens a novel direction to push the boundaries of simulation based studies by leveraging the power of LLMs to capture human subjective preferences. As LLMs continue to develop, RecAgent can be further enhanced as we provide a flexible interface to incorporate any LLM. We believe this is a fundamental direction, which can shift the paradigm of recommendation studies from methods dominated by real-data to strategies combining real-data and simulation.

⁵https://github.com/google-research/recsim

⁶https://github.com/eyounx/VirtualTaobao

Table 1: The results of evaluating sensory memory (T1), short-term memory (T2), and long-term memory (T3). A and B indicate the results generated by the agent and real human, respectively. ">>", ">", and " \approx " mean significantly better, slight better and comparable, respectively.

	A >> B	A > B	$A \approx B$	B > A	B >> A
T1	0.6833	0.2500	0.0333	0.0333	0.0000
T2	0.3000	0.3000	0.1000	0.2500	0.0500
T3	0.2500	0.1167	0.2000	0.2500	0.1667

Furthermore, recommender system is just a sub-field of human-centered AI, and user simulation should be a pervasive challenge across all tasks in this domain. We believe RecAgent can serve as an example to inspire researchers tackling other subjective simulation problems in human-centered AI.

3 Experiments

To evaluate the effectiveness of our simulator, we conduct extensive experiments from both agent and system perspectives. From the agent perspective, we evaluate the effectiveness of different types of memories and measure whether the agent can invoke informative and relevant memories based on different memory structures. From the system perspective, we focus on the reliability of our generated user behaviors, and also evaluate the simulation efficiency. At last, we present several case studies to show the effectiveness of system intervention.

3.1 Agent-level Evaluation

In this experiment, we evaluate the agent with a focus on the memory module. In specific, we first conduct independent evaluations for each component in the memory module discussed in section 2.1.2, and then assess the information extracted from the complete memory module.

3.1.1 Evaluation of each component in the memory module

To evaluate whether sensory memory, short-term memory, and long-term memory can effectively fulfill their respective functions, we first let three real humans and one agent to perform identical memory-related tasks, and then let another group of real humans to judge which results are more reasonable. In the first phase, for the sensory memory, we focus on its information summarization capability, and ask real humans to manually summarize the raw observations according to the agent profiles (T1). For the short-term memory, we focus on its insights generation capability, and ask real humans to summarize insights based on the memory record and the ones used to enhance it (T2). For the long-term memory, we focus on its reflection capability, and ask real humans to manually write the reflections (T3). For each of the above task, we randomly select 20 cases in the simulation process for evaluation. Thus, after the first phase, we can obtain 60 human results. In the second phase, for each human result, we pair it with the corresponding agent result, and recruit another three human annotators to evaluate which one is better. In each pair of results, the annotators do not know which one is produced from the agent, and they have to make a selection from the following options: (1) the former is significantly better than the latter, (2) the former is slightly better than the latter, (3) The former is comparable to the latter, (4) the latter is slightly better than the former, (5) the latter is significantly better than the former. At last, we compute the ratio of each option for each task.

Result analysis. The results are presented in Table 1, from which we can see: for the sensory memory, most annotators (about 93%) believe that the summarization capability of the agent can outperform that of the real human's. This result is quite encouraging, and suggests that summarization is not a hard problem for the agent, and thus, simulating human sensory memory is feasible in RecAgent with the help of LLMs. For the short-term and long-term memories, about 70% and 56% annotators believe that the agent can produce better or comparable results than the real human. Comparing with the summarization task in T1, generating insights in T2 and T3 can be more difficult, which focuses on human high-level cognitive processes. We believe this could be an important reason to explain why the positive results of T2 and T3 is smaller than that of T1. However, if we observe the absolute values, 70% and 56% can sufficiently demonstrate that the agent can achieve human-level capability

Table 2: The results of evaluating the memory module. We use bold fonts to label the best results.

Model	Informativeness	Relevance	
Memory module (w/o short)	4.09	4.02	
Memory module (w/o long)	4.55	3.75	
Memory module (w/o reflection)	4.40	3.63	
Memory module	4.42	4.09	

on insight generation. Based on all the above results, we may conclude that, for each single memory, our designed agent can better or comparably fulfill its function as compared with real humans.

3.1.2 Evaluation of the complete memory module

Beyond the above experiments on evaluating each component in the memory module independently, we also assess the extracted information from the complete memory module. In specific, we evaluate whether the designed memory mechanism can produce informative and relevant knowledge to support user behaviors. For example, if an agent would like to select movies from a recommendation list, then she should recall sufficient and relevant memories to help her to make decisions. To see the advantages of our memory module, we compare it with its three variants: (1) in <u>w/o short</u>, we remove the short-term memory, and the final extracted information is only from the long-term memory, (2) in <u>w/o long</u>, we remove the long-term memory, and the final extracted information is only from the short-term memory, (3) in <u>w/o reflection</u>, we inactivate the reflection mechanism in long-term memory. We randomly sample 15 agent behaviors like movie selection, friend chatting and posting message, and use them as the testing cases. For each case, we recruit three human annotators to evaluate the extracted information from different variants. We ask each annotator to answer the following two questions:

Question 1: For the current behavior, whether the extracted memories are informative? **Question 2**: For the current behavior, whether the extracted memories are relevant?

Each annotator is required to give a score from 1 to 5 for each question. Then, we average the scores across all the annotators and testing cases for each variant.

Result analysis. The results are presented in Table 2, from which we can see: if we remove the short-term memory, the informativeness score is severely lowered. We speculate that the short-term memory may have stored a lot of diverse user recent memories. According to section 2.1.2, all the short-term memory information is extracted. Thus, the obtained memories can be more comprehensive and informative. On the other hand, since the long-term memory is extracted based on embedding similarities, the obtained information can be highly relevant with the current user behavior. As a result, we can see, if we remove the long-term memory or the reflection information, the relevance scores are lowered. By combining all the memory components, our complete memory module can achieve the best relevance score, and a comparable informativeness score to the best one. The above results demonstrate the rationalities of our design on the memory module to incorporate different memory components.

3.2 System-level Evaluation

In the above sections, the experiments mainly focus on a single agent. In this section, we broaden the evaluate scope, and evaluate the behaviors of multiple agents from the system perspective. In specific, we first evaluate whether the agents can effectively discriminate the real-user interacted items from the irrelevant ones. Then, we assess whether RecAgent can autonomously generate reliable user behaviors. The first experiment aims to evaluate the discrimination capability of RecAgent, while the second one is designed to test its generation capability, which is much harder. In the next, we evaluate the simulation efficiency by varying the number of agents and API keys. At last, we present several case studies to show the effectiveness of system intervention.

Table 3: The results of evaluating different models based on different (a, b) 's	Table 3: The r	esults of evaluat	ing different r	nodels based or	different	(a,b)'s.
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Model	(a,b) = (1,5)	(a,b) = (3,3)	(a,b) = (3,7)	(a,b) = (1,9)
Embedding	0.2500	0.5500	0.4500	0.3000
RecSim	0.2500	0.5333	0.3667	0.1000
RecAgent	0.5500	0.7833	0.6833	0.5000
Real Human	0.6000	0.8056	0.7222	0.5833

3.2.1 Evaluation on the discrimination capability of RecAgent

To evaluate the discrimination capability, we first sample 20 users as well as their interactions from a well-known recommendation dataset Movielens- $1M^7$. Then, for each user, we leave her last a items as the evaluation ground truths, and use all the other items to initialize the agent profiles. For evaluation, we combine the ground truths with b negative items to form a recommendation list containing (a+b) items. We present the recommendation list to the agent, and let it select a items to compare with the ground truth. Suppose, for a user u, the ground truth and selected item sets are T_u and S_u , respectively, then we use the following metric to evaluate different models:

$$p = \sum_{u \in U} \frac{|T_u \cap S_u|}{|T_u|},$$

where U is the set of all users, and larger p indicates better performance. In the experiments, we set a and b with various values to more comprehensively evaluate our simulator. In intuitively, selecting a smaller number of ground truth from a larger pool of candidates should be more difficult.

Different from traditional recommender models, which aims to generate recommendation lists to users, RecAgent is basically a user model, which targets at making selections from given recommendation lists. As a result, we compare RecAgent with the following models:

- Embedding [25]: in this method, for each user, we leverage the average embedding of her interacted items as the user model. When making selections, we compute the inner product between the user model and candidate item embeddings. The item embeddings are derived based on the movie descriptions using Sentence-BERT [33].
- **RecSim** [19]: This is a well-known recommender simulator developed by Google Research. In this method, we first initialize the user vectors in a similar manner as the above model's, and then run the toolkit with default settings.
- **Real Human**: in this method, we present the user previous interactions and the current movie description to real humans, and let them make selections from the recommendation list. To remove randomness, we recruit three humans, and average their performance results.

Result analysis. The experiment results are presented in Table 3, from which we can see: for different (a,b)'s, the Embedding method is comparable with RecSim, while by using LLMs, RecAgent can significantly improve the performances. This result is as expected, and agrees with the previous studies, which have demonstrated the potential of LLMs on achieving human-like intelligence across different tasks. By this experiment, we verify that LLMs can also help to simulate user preferences and behavior patterns accurately. If one compare the results of RecAgent and Real Human, she may find that their gaps are not large. On average, the performance of RecAgent can surpass the best baseline by about 68%, but is only 8% lower than the results of Real Human. These results are encouraging, and demonstrate that RecAgent may have made an important step towards much more accurate user simulation in the recommendation domain.

3.2.2 Evaluation on the generation capability of RecAgent

In this experiment, we aim to evaluate whether RecAgent can generate reliable user behaviors. Different from the above experiment, where each agent only makes a one-step action to separate the ground truth with the other items, here, we let each agent generate a sequence of behaviors. Similar to the above experiment, we sample 20 users and their interactions from Movielens-1M. We leave the

⁷https://grouplens.org/datasets/movielens/1m/

Table 4: The results of evaluating the reliability of the generated user behavior sequences (N=5).

A v.s. B	A >> B	A > B	$A \approx B$	B > A	B >> A
RecAgent v.s. RecSim	0.1500	0.3167	0.1833	0.2667	0.0833
RecAgent v.s. GT	0.1333	0.2833	0.1667	0.2667	0.1500
RecSim v.s. GT	0.1167	0.2667	0.2667	0.2167	0.1333

Table 5: The results of evaluating the reliability of the generated user behavior sequences (N=10).

A v.s. B	A >> B	A > B	$A \approx B$	B > A	B >> A
RecAgent v.s. RecSim	0.1833	0.4333	0.0667	0.2000	0.1167
RecAgent v.s. GT	0.2000	0.4333	0.0000	0.2000	0.1667
RecSim v.s. GT	0.1333	0.3500	0.1500	0.3000	0.0667

last N items of each user as the ground truth, and use the other ones to initialize the agent profile. We execute multiple rounds of RecAgent, and at each round, we first generate a recommendation list containing five movies based on MF [25], and then the agent autonomously selects one of them. Each agent totally acts N steps, generating an N-length behavior sequence. We compare RecAgent with RecSim and the ground truth, and ensure that the executions of RecSim and RecAgent are based on the same settings (e.g., the recommender model, the length of the generated sequence, and so on).

To evaluate the quality of the generated sequences, we recruit three human annotators to make paired comparisons among RecAgent, RecSim and the ground truth (GT), that is, (1) RecAgent v.s. RecSim, (2) RecAgent v.s. GT and (3) RecSim v.s. GT. For each pair of comparison, the annotators are given: (1) the previously interacted movies of the agent as well as their descriptions, and (2) two user behavior sequences without identifying which one is from RecAgent, RecSim or GT. They are required to answer the following question:

Question: Please compare the two behavior sequences according to the agent preference reflected in its previous interactions. You can select one from the following options: (1) the former is significantly better than the latter, (2) the former is slightly better than the latter, (3) The former is comparable to the latter, (4) the latter is slightly better than the former, (5) the latter is significantly better than the former.

We report the ratio of each option in all the annotation results for each pair of comparison. To evaluate the influence of different sequence lengths, we set N as 5 and 10 in the experiments.

Result analysis. The results are presented in Table 4 and 5. From the comparison between RecAgent and RecSim (*i.e.*, RecAgent v.s. RecSim), we can see, when N=5, about 47% annotation results (*i.e.*, "A >> B" + "A > B") believe that RecAgent is better than RecSim, while 34% results (*i.e.*, "B >> A" + "B > A") suggest that the winner is RecSim. When N=10, the support ratios of RecAgent and RecSim are 61% and 31%, respectively. These results demonstrate the superiority of RecAgent, and as the generation sequence becomes longer, the advantage is more significant. From the comparison between RecAgent and GT (*i.e.*, RecAgent v.s. GT), we can see, when N=5, the support ratios of RecAgent and GT are about 41.6% and 41.7%, respectively, which suggests that human annotators cannot significantly separate the results of RecAgent from the ground truth. When N=10, human annotators even believe the results of RecAgent is better than the ground truth, where their support ratios are about 63% and 36%, respectively. By jointly analyzing the results of RecSim v.s. GT and RecAgent v.s. GT, we can see, if we take GT as a reference, RecAgent is better than RecSim for both N=5 and N=10, which agrees with the results of RecAgent v.s. RecSim.

3.2.3 Efficiency analysis

Beyond the above experiments on simulation effectiveness, we also analyze the efficiency of our simulator to provide more insights. In specific, we focus on the following four problems:

- P1: How does the time cost increase as the number of agents become larger in each epoch?
- P2: How does the time cost increase as the number of API keys become larger in each epoch?

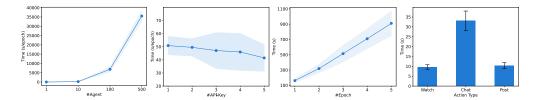


Figure 6: The results of efficiency analysis of our simulator.

- P3: How does the time cost increase as the number epochs become larger?
- P4: What are the time costs of different agent behaviors?

For the first problem, we fix the number of API keys as 1, and observe the time cost of one round execution of our simulator when the number of agents ranges from 1 to 500. In our simulator, we support parallel API key invocation. For the second problem, we fix the number of agents as 10, and observe the time cost of one round execution when the number of API keys ranges from 1 to 5. In the third problem, we observe the total simulation cost as the number of epochs becomes larger, where we fix the number of API keys and agents as 1 and 10, respectively. In the forth problem, we analyze the time costs of different agent behaviors, where the settings on API keys and agents follow the above experiment, and we focus on three types of behaviors including "movie selection", "friend chatting" and "message posting". In this experiment, we run our simulator on a server equipped with 6 CPUs (Intel(R) Xeon(R) Gold 6148 CPU @ 2.40GHz) and 4GB of memory.

Result analysis. The results are presented in Figure 6. We can see, when the number of API keys is fixed, the time cost increases as the number of agent becomes larger. For example, when we deploy 10 agents, the time cost is about 220s for each round of simulation, while when we have 100 agents, the simulation time becomes 1.9 hours under the same setting. It should be noted that, in this experiment, we make all agents take actions. In practice, the number of active agents can be much smaller as discussed in section 2.2.1, which may greatly lower the time cost. By incorporating more API keys, the time cost can be lowered, which demonstrates the effectiveness of our designed mechanism for parallel API key invocation. However, we find that the results fluctuate a lot, and the variance is high, which is perhaps due to the unstable network speeds. As the number of rounds becomes larger, the time cost rises with an increasing acceleration rate, possibly because the information gradually accumulates as we run the simulator, which may lead to longer processing time. Among different types of behaviors, "friend chatting" costs most, since it needs to generate more complex contents. In practice, we found that 10 agents cost about 0.25 dallors per round based on ChatGPT, and the cost increases almost linearly as the number of agent becomes larger.

3.2.4 Case studies on system intervention

As discussed in section 2.2.4, our simulator allows external interventions. In this section, we evaluate whether such interventions can effectively change agent behaviors as expected. In specific, we change the agents' profile information, and observe how their behaviors can be influenced. In the experiments, we first run our simulator for five rounds, and then separate the simulation into two branches: in the first branch, we change the agent profile information (**Intervention Branch**), while in the second branch, we do not make any intervention (**Original Branch**). For each branch, we continue to run our simulator for five rounds. At last, we compare the differences between these two branches in the scenarios of friend chatting.

We present the results in Figure 7. In the left case, we change the traits and interests of an agent called David Smith. Originally, David Smith likes sci-fi movies. Thus, we may find sentences like "I did watch this amazing sci-fi thriller called <Inception>. It's mind-blowing!" or "I'm more into sci-fi, thriller, and suspense movies. They always keep me on the edge of my seat." in his dialogs. However, if we change his preference to be a lover of family-friendly movies, then we observe sentences like "By the way, have you come across any good family-friendly or romantic movies? I'm in the mood for something heartwarming.". In the right case, we can find similar results. After introducing sci-fi, thriller and action movies into the agent's preference, it says "I've always loved the thrill and excitement of sci-fi, thriller, and action movies. They really get my adrenaline pumping".

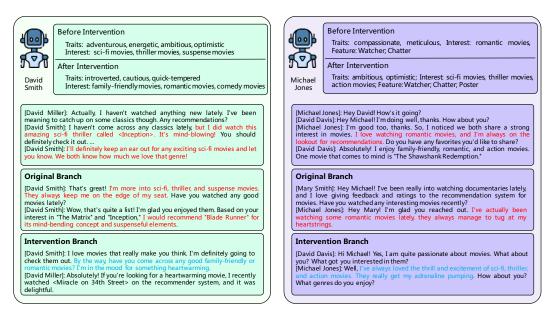


Figure 7: Case studies on system intervention in the scenarios of friend chatting. The gray-colored region indicates the dialogs of the agent discovered in the first five round execution.

In addition to compare the chatting behaviors before and after the intervention, we also actively interview the agents to let it recommend a movie to the others, and explain the reasons. Ideally, the agent should make recommendations according to its own preference, and if its preference has been changed, the recommended movies should be accordingly altered. We interview the same agents as the above experiment. The results are presented in Figure 8. For both cases, we can see, the agent can successfully change its recommended movies according to its preference. In addition, the recommendation reasons suggest that the recommendation changes are exactly because of the preference differences before and after the intervention.

4 Related Work

4.1 Recommender Systems

In the age of information explosion, recommendation systems have become an indispensable part of our lives. Recommendation systems can proactively suggest products to users based on their historical behavior and personal preferences, thus addressing the issue of information overload [8, 34, 24]. In the past few decades, people have designed a large amount of recommender models, focusing on different settings and scenarios. In specific, content-based algorithms are among the earliest methods employed in recommendation systems. They recommend products similar to those the user has previously shown interest in [23, 29]. Collaborative filtering (CF) is the most classic recommendation algorithm, which relies on the similarity between users and items to make recommendations [15, 40]. In specific, user-based CF relies on the historical behavior of users, recommending items liked by other users with similar interests to the target user [50]. Item-based CF, on the other hand, relies on item similarity, recommending items that are similar to those liked by the user [36]. Sequential recommendation focuses on predicting the next behaviors of the users based on their history actions [44, 20]. Graph-based recommendation leverages the graph structure of relationships between items or users to discover potential connections and recommend relevant contents [47, 14]. Conversational recommendation understands user preferences by interactive dialogs, and makes the final recommendation based on all the collected user opinions [41, 11]. Basically, most of the above algorithms aim to design system models to solve the problem of how to generate recommendations. However, we focus on simulating user behaviors, that is, how different users may behave in a recommender system, for example, given a recommendation list, how they make selections.



Traits: adventurous, energetic, ambitious, optimistic, Interest: sci-fi movies, thriller movies, suspense movies

The recommended movie:

Eternal Sunshine of the Spotless Mind

Recommendation reason:

The reason is David Smith's traits include being adventurous, energetic, ambitious, and optimistic. This movie is a sci-fi romance that combines David's interest in sci-fi movies with a touch of romance. The film explores the concept of erasing memories and has a unique and mind-bending storyline that will captivate David's adventurous spirit. The movie also delves into the complexities of relationships and the power of memories, providing a thought-provoking and emotionally satisfying experience.



Traits: compassionate, meticulous, Interest: romantic movies, Feature: Watcher; Chatter

The recommended movie:

Titanio

Recommendation reason:

The reason is Michael Jones, being a compassionate and meticulous individual, would appreciate a movie like <Titanic>. The movie is known for its emotional impact and compelling storyline, which aligns with Michael's values. The tragic love story depicted in <Titanic> showcases the depth of human emotions, and Michael would resonate with the characters and their experiences. Additionally, as Michael actively engages in watching and discussing romantic movies, <Titanic> is a classic choice in this genre.



Traits: introverted, cautious, quick-tempered, Interest: family-friendly movies, romantic movies, comedy movies

The recommended movie:

Miracle on 34th Street

Recommendation reason:

The reason is David Smith's interest in family-friendly and heartwarming movies aligns perfectly with the movie "Miracle on 34th Street." This movie is a classic holiday film that showcases the power of belief and the magic of Christmas. It is a heartwarming story that can be enjoyed by all ages and is known for spreading joy and positivity. David Smith's cautious and introverted nature may appreciate the movie's gentle and feel-good atmosphere.



Traits: ambitious, optimistic; Interest: sci-fi movies, thriller movies, action movies; Feature: Watcher; Chatter; Poster

The recommended movie:

Inception

Recommendation reason:

The reason is <Inception> is a sci-fi thriller that perfectly aligns with my interests. The movie's mind-bending concept and intricate plot captivate me, and the action sequences keep me on the edge of my seat. Additionally, the movie explores themes of ambition and the power of dreams, which resonate with my own drive for success. Overall, <Inception> satisfies my love for thrilling storylines and leaves me wanting more.

Figure 8: Case studies on system intervention by actively interviewing the agents.

4.2 User Simulation

User modeling and simulation has always been a crucial aspect of research in recommendation systems [39, 7]. Enabling interactions between simulated users and recommendation systems to generate synthetic data can help in constructing simulators to address issues such as the high cost and risk of training and testing recommendation systems in online environments, as well as dealing with sparse historical data [21, 39, 17]. It also facilitates research into counterfactual questions, such as exploring "what-if" scenarios to investigate the effects of specific interventions on the recommender system and user behavior [1, 30, 6]. RecSim [19], which leverages reinforcement learning, focuses on simulating user behavior in real-world situations and can simulate sequential interactive recommendations. RecoGym [35], on the other hand, is a reinforcement learning environment designed for recommender system, modeling traffic patterns of users in e-commerce, and can support both online and offline experiments. In contrast to previous RL-based approaches, Virtual Taobao [38] is trained on real data from Taobao. It generates a virtual user each time to decide whether to click on the item recommended by the recommender system. Different from the previous work, we leverage LLMs to simulate user subjective preference and behavior patterns, and introduce a series of modules to design LLM-based autonomous agents for user simulation.

4.3 LLM-empowered Autonomous Agent

The LLM-empowered autonomous agent has recently garnered significant attention [43]. Agents are widely applied in various scenarios and applications, such as autonomous software development [31, 16, 12], serving as tools to assist humans in accomplishing specific tasks [37, 32, 22], and act as a planner to break down complex tasks and generate executable plans [3, 51, 27]. An innovative application involves constructing a simulation environment composed of agents, where multiple agents can autonomously take action and interact with each other [28, 13]. Researchers are actively exploring the integration of agents with recommendation systems as well. For instance, [45, 18] involve agents at different stages of recommendations to enhance recommendation effectiveness. Different from these studies, we aim to simulate user behaviors, and build comprehensive modules and environments to enable them to act like real humans.

5 Limitations

This paper may have the following limitations, which can be addressed in the future work.

The real-world continuous time is discretized in our simulator. The execution of our simulator follows a round-by-round approach. While we do consider time information, it is discretized, which deviates from reality. This approximation restricts users from taking actions between rounds, resulting in less flexibility compared to real-world scenarios.

Not all factors relevant with the user recommendation decisions are simulated. RecAgent solely focuses on simulating user behaviors within the recommender system and social media. However, we may overlook various factors that also impact user decisions within the recommender system. For instance, a father may choose to accompany his son while watching cartoons, even if they are not of personal interest to him.

The LLMs used in our simulator is not tailored to the recommendation problem. Our simulator does not include specific fine-tuning of the LLMs to enhance their adaptiveness to recommendation problems. To achieve acceptable simulation effectiveness, we have carefully designed the prompts for different user behaviors. However, these prompts may not be robust for different LLMs. For instance, ChatGPT and GPT-4 may require distinct prompts.

6 Conclusion and Future Work

This paper introduces a novel simulation study paradigm in the field of user behavior analysis, specifically focusing on recommender systems. We have developed an LLM-empowered simulator called RecAgent. RecAgent simulates various user behaviors that are highly relevant to the user actions and decisions within the recommender system. To ensure effective simulation, we have meticulously designed the structure of the agent and the system environment. Extensive experiments have been conducted to demonstrate the effectiveness of our simulator. This paper takes the initial step towards simulating user behaviors based on LLMs. There is much room left for improvement. For instance, one can fine-tune existing LLMs to enhance their capabilities for following instructions within the recommendation domain. In addition, people can also extend RecAgent to the other tasks in human-centered AI, for example, social network analysis, information retrieval, and among others.

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7 Appendix

7.1 Examples of RecAgent

7.1.1 An example of the first step in sensory memory

Suppose the observation is a dialogue between David Miller and David Smith as follows:

OB: [David Smith]: Hey David! I recently watched some mind-blowing movies on the recommender system. Have you seen any of these: <Interstellar>, <Inception>, <The Matrix>, <Blade Runner>, or <The Prestige>?

[David Miller]: Oh, hey David! Yes, I actually watched <Interstellar> and <Inception> recently, and they were absolutely amazing! The visuals, storytelling, and mind-bending concepts were mind-blowing. I'm so excited to discuss them with you!

[David Smith]: That's great to hear! I completely agree, those movies are truly mind-blowing. I'm glad you enjoyed them too. I was blown away by the visuals and the way they explore complex ideas. Do you have any other mind-blowing movie recommendations?

[David Miller]: Definitely! If you loved those movies, I think you'll also enjoy <The Matrix>, <Blade Runner>, and <The Prestige>. They have similar mind-bending concepts and incredible storytelling. I can't wait to watch them and discuss them with you!

[David Smith]: Awesome! I've heard great things about those movies as well. Let's make a plan to watch them together and have a movie night. It'll be so much fun to dive into these mind-blowing films and share our thoughts.

[David Miller]: Absolutely! I'm really looking forward to it. We can also invite some other movie enthusiasts to join us and make it a movie marathon. The more, the merrier!

[David Miller]: You're welcome, David. I'm glad too. See you soon and get ready for an unforgettable movie marathon!

Then, we use the following prompt to compress this observation based on LLMs:

Prompt: The observations are as following: {OB}. You should summarize the above observation(s) into one independent sentence. If there is a person's name in the observation, use third person, otherwise use first person. Note that the sentence should pay more attention to the movie interest and the reasons in the observations. The summarization should not include the profile explicitly.

As last, the compressed observation is:

Output: Two individuals, David Smith and David Miller, engage in a conversation about their shared passion for mind-blowing movies, discussing and recommending films such as Interstellar, Inception, The Matrix, Blade Runner, and The Prestige, ultimately planning a movie night and inviting others to join them for a movie marathon.

7.1.2 An example of the insight generation process in short-term memory

Suppose a memory record

MR: David Miller is interested in mind-bending movies like <Interstellar> and <Inception> and is looking for recommendations from fellow movie lovers to explore more in this genre.

has been enhanced by the following records:

OB: 1. David Smith is recommending the mind-blowing films <Interstellar> and <Inception> that he recently watched on a recommender system, and is seeking further recommendations to explore and discuss.

- 2. David Miller enjoyed watching the movies <Interstellar> and <Inception> on the recommender system and found them mind-blowing, prompting him to seek further movie recommendations.
- 3. David Smith expressed his interest in movies, particularly mentioning <Interstellar> and <Inception>, seeking recommendations and thoughts from others.

Then, we use the following prompt to generate insights based on LLMs:

Prompt: There are some memories {MR, OB}. Can you infer from the above memories the high-level insight for this person's character? The insight needs to be significantly different from the content and structure of the original memories. Respond in one sentence. Response in one line.

At last, the output is:

Insight: David Miller is a curious and open-minded individual who actively seeks recommendations and discussions about mind-bending movies.

7.1.3 Example curves of $g(M_i)$

For an intuitive understanding of the forgotten mechanism in long-term memory, we present several examples of the curve of $g(M_i)$ in Figure 9.

7.2 Prompt Examples for different Agent Behaviors

The prompt used in RecAgent consists of three parts: a summary of the Agent's personal profile, reaction to given observation, and action-specific instructions.

7.2.1 Summary

Summary is the process of extracting and summarizing information relevant to the current observation from the user's profile.

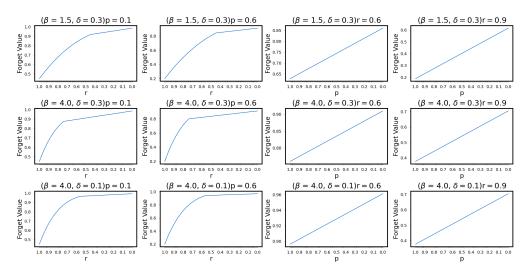


Figure 9: Examples of the curve of $g(M_i)$ with different hyper-parameters.

Summary: Given the following observation about David Miller: 'David Smith is going to chat with David Miller.', please summarize the relevant details from his profile. His profile information is as follows:

Name: David Miller

Age: 39 Gender:female

Traits: fun-loving, creative, practical, energetic, patient

Status: writer

Movie Interest: action movies, sci-fi movies, classic movies

Feature: Choose movies, enjoy watching, and provide feedback and ratings to the recommendation system. Search for movies heard of before and expand movie experiences...Enjoy publicly posting on social media and sharing content and insights with more people.

Interpersonal Relationships: 'David Smith': 'friend' Please avoid repeating the observation in the summary.

Summary:

Output: David Smith is a 25-year-old male photographer who is compassionate, caring, ambitious, and optimistic. He has an interest in sci-fi and comedy movies and enjoys choosing, watching, and providing feedback and ratings to the recommendation system. He has high standards for movies and the recommendation system and may criticize both. He has a friendship with David Miller.

7.2.2 Reaction

This section serves as a shared prompt framework for all actions, integrating information such as summary, memory, observation, and more to obtain the agent's reaction. It covers reactions for both individual agent actions and dialogues involving two agents.

• Single Agent Reaction

Reaction: Name: David Smith (age: 25) {Summary}

It is September 12, 2023, 08:00 AM.

David Smith recently heard [The Matrix, Back to the Future., Anchorman, Superbad] on social media.

David Miller recently watched nothing on recommender system. Other than that David Miller doesn't know any movies.

Most recent observations: David and Millar had a conversation about their shared interest in movies, discussing their favorite genres such as sci-fi, comedy, and action, exchanging recommendations, expressing their skepticism about recommendation systems, and making plans to compare notes and potentially organize a movie night together. David Miller is seeking recommendations for movies such as "The Matrix," "Back to the Future," "Anchorman," and "Superbad" on social media, expressing interest in planning a movie night and inviting others to share their thoughts and suggestions.

Observation: David Miller want to post for all acquaintances. All occurrences of movie names should be enclosed with <>

• Reaction Between Two Agent

Reaction: Name: David Smith (age: 25)

Summary

Name: David Miller (age: 39)

Summary

It is September 12, 2023, 10:28 PM.

David Smith recently heared [Ínception, The Dark Knight, Ínception, The Dark Knight] on

social media.

David Smith recently watched nothing on recommender system.

Other than that David Smith doesn't know any movies.

David Miller recently heard [Ínception; The Dark Knight] on social media. David Miller recently watched nothing on recommender system. Other than that David Miller doesné know any movies.

Most recent observations of David Smith: David Smith observed that David Miller was interested in chatting about movies, as evidenced by his action of initiating a chat conversation. David and David had a conversation about their mutual interest in movies, with David Miller recommending sci-fi and action films like "Inception" and "The Dark Knight" to David Smith, who expressed interest in watching them and sharing his thoughts with David Miller in the future. David Miller is excited to watch and review <Inception> and <The Dark Knight> after discovering them on his recommender system. David Smith observed that David Miller had a chat about movie interests, focusing on the reasons behind their preferences.

Most recent observations of David Miller: David Miller and David Smith had a conversation about their shared interest in movies, with David Miller recommending sci-fi movie "Inception" and action movie "The Dark Knight" to David Smith, who expressed interest in watching them and discussing them later.; David Miller expressed his excitement about two highly recommended movies, "Inception" and "The Dark Knight," which he discovered on social media, and eagerly anticipates watching them and sharing his reviews with others.; David Miller is excited to watch and share his reviews of the movies <Inception> and <The Dark Knight> that he discovered on his recommender system.

Observation: David Smith is going to chat with David Miller.

All occurrences of movie names should be enclosed with <>.

7.2.3 Action

This section includes all the actions that agents can perform, along with examples of input and output for each action. • 1. Take Action

OB: David Miller must take only ONE of the actions below: (1) Enter the Recommender System. If so, David Miller will be recommended some movies, from which David Miller can watch some movies, or search for movies by himself.

- (2) Enter the Social Media. David Miller can chat with friends or publish a post to all friends of David Miller. If David Miller recently watched some movies they might want to share with others.
- (3) Do Nothing.

Suffix: What action would David Miller like to take? Respond in one line.

If David Miller wants to enter the Recommender System, write:

[RECOMMENDER]:: David Miller enters the Recommender System

If David Miller wants to enter the Social Media, write:

[SOCIAL]:: David Miller enters the Social Media

If David Miller wants to do nothing, write: [NOTHING]:: David Miller does nothing

Output: [RECOMMENDER]:: David Miller enters the Recommender System.

• 2. Take Recommender Action

OB: David Smith is browsing the recommender system. David Smith is recommended ["<Eye of Vichy, The (Oeil de Vichy, L')>||The movie <Eye of Vichy, The (Oeil de Vichy, L') > is a documentary that delves into the propaganda films made by the Vichy government during World War II.", "<Oliver!>||<Oliver!> is a musical adaptation of Charles Dickens' classic novel <Oliver Twist>.", '<...And Justice for All>||<...And Justice for All> is a legal drama film from 1979 that follows the story of an ethical and idealistic defense attorney named Arthur Kirkland, played by Al Pacino. Kirkland finds himself in a moral dilemma when he is forced to defend a judge who he despises, who has been accused of rape. As he navigates the corrupt legal system and grapples with his own values, Kirkland must decide whether to compromise his integrity or risk losing everything he has worked for. The film explores themes of justice, morality, and the flaws of the American legal system.', '<T-Men>||<T-Men> is a film noir about two Treasury agents who go undercover to break up a counterfeiting ring.', '<Son of Flubber>||<Son of Flubber> is a 1963 American comedy film directed by Robert Stevenson and starring Fred MacMurray.'].

Suffix: David Miller must choose one of the four actions below: (1) Watch ONLY ONE movie from the list returned by the recommender system.

- (2) See the next page.
- (3) Search for a specific item.
- (4) Leave the recommender system.

If David Miller has recently heard about a particular movie on social media, David Miller might want to search for that movie on the recommender system. To watch a movie from the recommended list, write: [BUY]:: ONLY ONE movie namelldescription. To see the next page, write: [NEXT]:: David Miller views the next page. To search for a specific item, write: [SEARCH]:: single, specific movie name to search for. To leave the recommender system, write: [LEAVE]:: David Miller leaves the recommender system.

Output: [BUY]::<Son of Flubber>||<Son of Flubber> is a 1963 American comedy film directed by Robert Stevenson and starring Fred MacMurray.

• 3. Generate Feeling

OB: David Jones has just finished watching S.F.W.;;S.F.W. (1994) is a dark comedy-drama film about a group of teenagers who are held hostage in a convenience store by a media-savvy, charismatic, and nihilistic young man, Cliff Spab (played by Stephen Dorff), and his equally disillusioned girlfriend, Wendy (played by Reese Witherspoon). The film explores themes of media manipulation, youth disillusionment, and the commodification of tragedy in modern society.

Suffix: David Jones, how did you feel about the movie you just watched? Describe your feelings in one line.NOTE: Please answer in the first-person perspective.

Output: I found "SFW" to be a thought-provoking and captivating exploration of media manipulation and youth disillusionment in modern society.

• 4. Search Item

OB: David Miller is browsing the recommender system. David Miller has searched for Interstellar in recommender system and recommender system returns item list:['Supernova (2000)', 'October Sky (1999)', 'Cat from Outer Space, The (1978)', 'Space Cowboys (2000)', 'Aliens (1986)'] as search results.

Suffix: David Miller must choose one of the four actions below:

- (1) Watch ONLY ONE movie from the list returned by the recommender system.
- (2) See the next page.
- (3) Search for a specific item.
- (4) Leave the recommender system.

If David Miller has recently heard about a particular movie on social media, David Miller might want to search for that movie on the recommender system.

To watch a movie from the recommended list, write:

[BUY]:: ONLY ONE movie name;;description

To see the next page, write:

[NEXT]:: David Miller views the next page.

To search for a specific item, write:

[SEARCH]:: single, specific movie name to search for.

To leave the recommender system, write:

[LEAVE]:: David Miller leaves the recommender system.

Output: [SEARCH]:: Inception

• 5. Generate Dialogue

OB: David Smith is chatting with David Miller.

Suffix: What will be said between David Smith and David Miller? David Smith initiates the conversation first. Please simulate their conversation.

David Smith and David Miller should not say anything about movies they have not watched or heard about.

Write the dialogue in the following format:

[David Smith]:

[David Miller]:

Output: [David Smith]: Hey David! How's it going? I heard you were interested in a movie. What's been on your mind?

[David Miller]: Hey David! I'm doing great, thanks for asking. Yeah, I've been hearing a lot about this movie <Interstellar> recently. Have you heard of it too?

[David Smith]: Absolutely! Actually, I've been seeing it all over social media as well. It seems to be a popular choice among movie lovers. I even watched it recently on the recommender system. The storyline was visually stunning and thought-provoking.

[David Miller]: That's awesome! I'm glad you enjoyed it. I've been wanting to watch it too. Would you be up for a cozy movie night to watch it together? We can discuss our thoughts and interpretations afterwards.

[David Smith]: I'd love that! It's always more fun to watch movies with friends and have those deep conversations afterwards. Count me in!

[David Miller]: Great! I'll make sure to set up a movie night soon. By the way, have you heard of any other movies that you'd recommend? I'm always open to expanding my movie experiences.

• 6. Publish Posting

OB: David Smith want to post for all acquaintances.

Suffix: Posts should be related to recent watched movies on recommender systems. David Smith should not say anything about movies that have not watched or heard about. If you were David Smith, what will you post? Respond in one line.

Output: Hey everyone! Just watched <Inception> on the recommender system and it was absolutely mind-blowing! Highly recommend checking it out!