Large Language Model Powered Agents for Information Retrieval

Tutorial at SIGIR 2024 in Washington D.C.

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July 14, 2024, Washington D.C., USA

Speakers

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Personal Information

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- **Education Background**
  - 2021 – present: **Post-Doc**, NUS, School of Computing, NExT++ Research Centre
  - 2016 – 2021: **Ph.D**, NUS, Department of Statistics and Data Science
  - 2012 – 2016: **B.S.**, Southeast University, School of Mathematics
- **Research Interests**: LLM-empowered Agents, Robust and Trustable AI, Recommender System
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Outline

- Part 1: Introduction of LLM-powered Agents
- Part 2: LLM-powered Agents with Tool Learning
- Part 3: LLM-powered Agents in Social Network
- **Part 4: LLM-powered Agents in Recommendation**
- Part 5: LLM-powered Conversational Agents
- Part 6: Open Challenges and Beyond

Significant Gap Between LLMs and Recommender Systems (RecSys)

- **Significant gap between large language models (LLMs) and recommender systems (RecSys).**

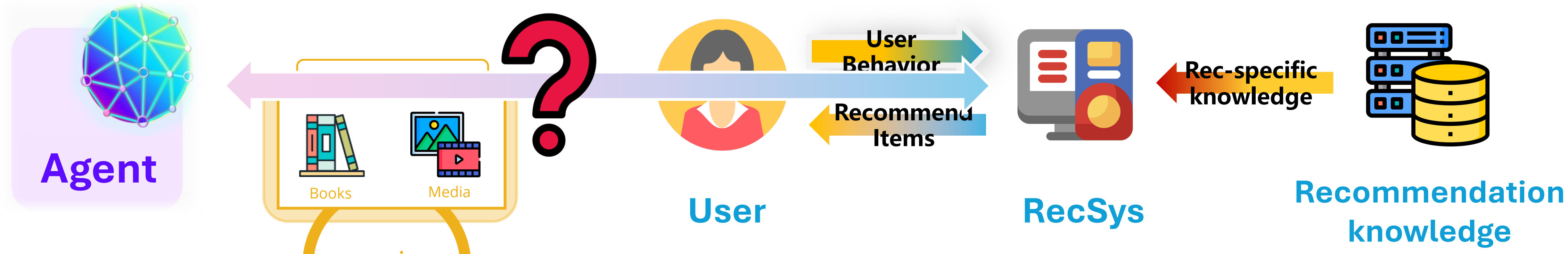
  How to bridge this gap?

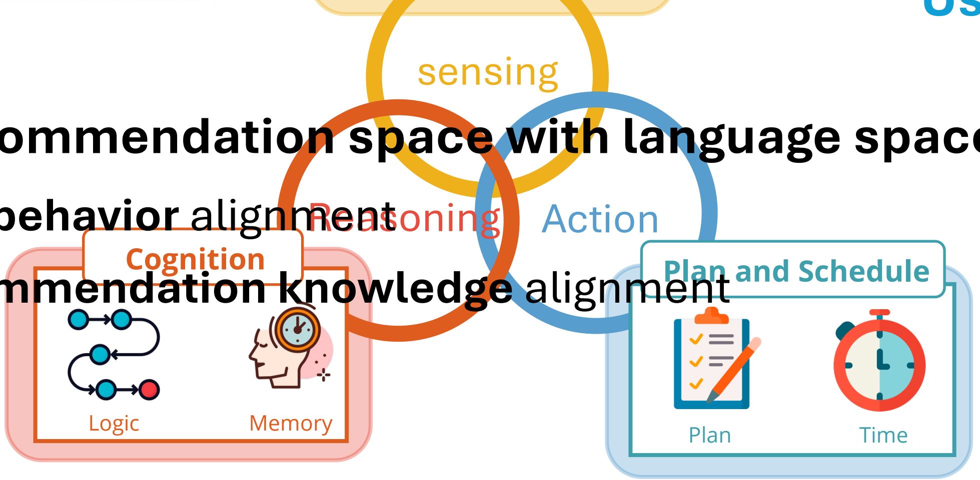
	LLMs	RecSys
Scope	Language modelling	User behaviour modelling
Data	Rich world text-based sources	Sparse user-item interactions
Tokens	A chunk of text (Ten thousand level)	Items (Billion level)
Characteristics	General model; Open-world knowledge; High complexity and long inference time;	Leveraging collaborative signals; Lack of cross-domain adaptability; Struggle with cold-start problem; Limited intention understanding;

Significant Gap Between LLMs and Recommender Systems (RecSys)

➢ **Significant gap between large language models (LLMs) and recommender systems (RecSys).**

How to bridge this gap?

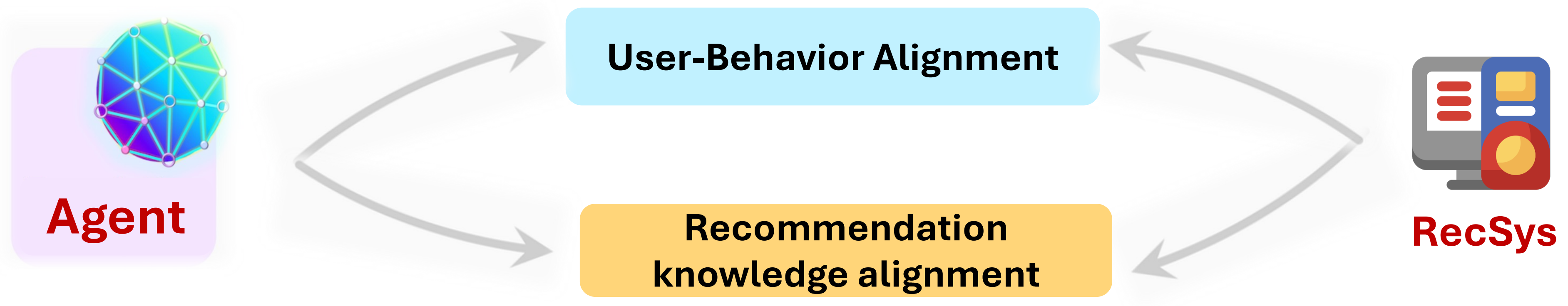




- **Align recommendation space with language space.**
  - **User behavior** alignment
  - **Recommendation knowledge** alignment

- **Two critical components in RecSys:**
  - Understanding **user's behavior/preference**
  - Acquiring recommendation-specific **knowledge**

LLM-powered Agents in Recommendation



- **LLM-powered Agents have potentials to solve long-standing problems in recommendation**
  - Can an LLM-powered Agent faithfully simulate **users**?
  - Can an LLM-powered Agent be a better **recommender** with recommendation-specific knowledge?

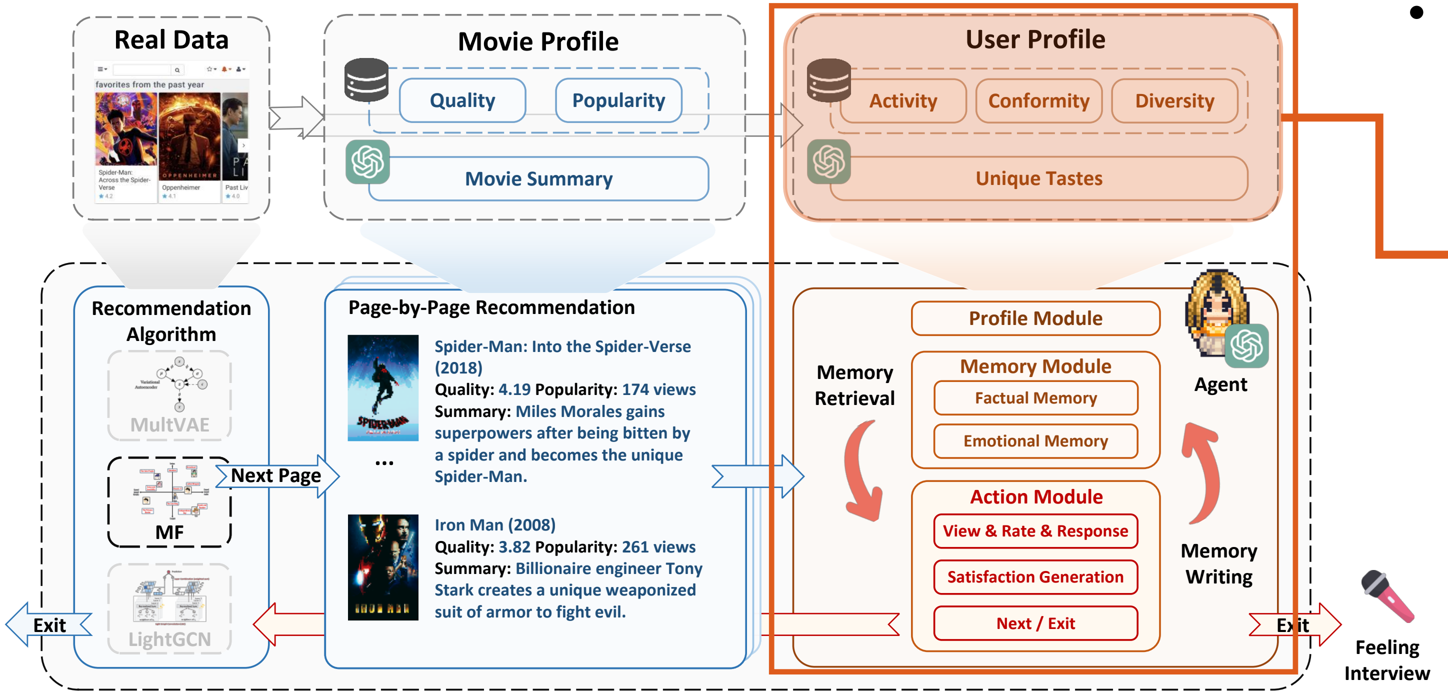
Agents as Users
Agent4Rec

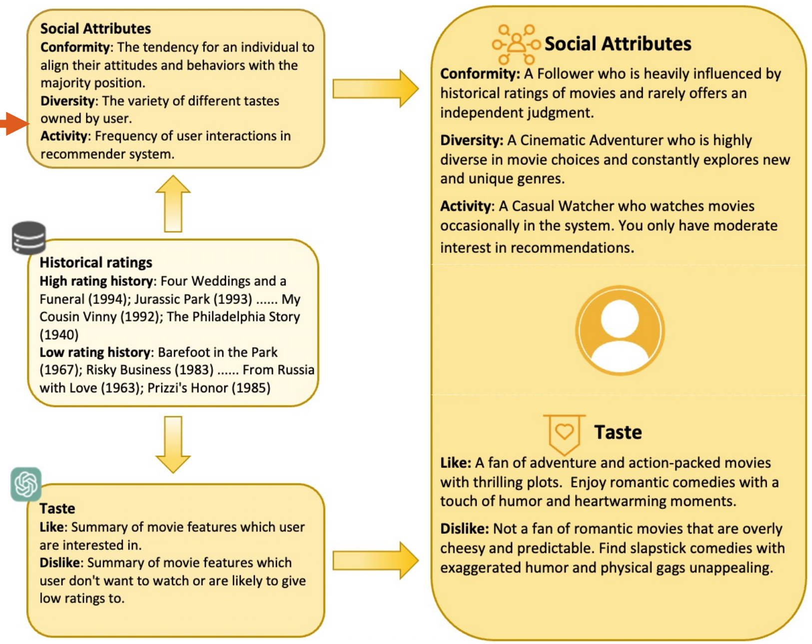
Agents as Users

❑ **Agent4Rec: Agent-driven user behavior simulation**

- **Key Points:**
  - Can LLM-powered Agent generate faithful user behaviors?

- **User Profile**: **1,000** LLM-empowered generative agents initialized with **real data** in various dataset and augmented by ChatGPT.
- **Item Profile**: Statistical information in dataset and generated summary.





An Zhang et al. On Generative Agents in Recommendation. SIGIR 2024.

Agents as Users
Agent4Rec

Agents as Users

❑ **Agent4Rec: Agent-driven user behavior simulation**

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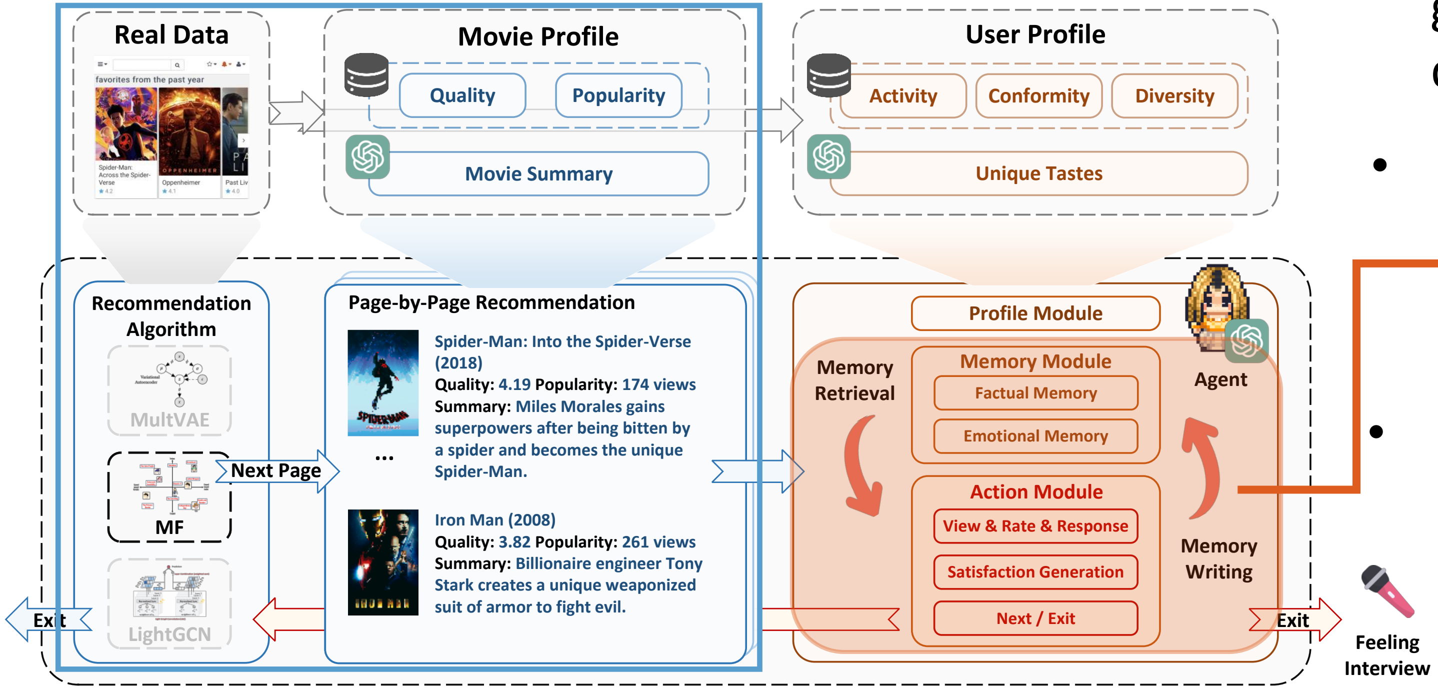


- Agents as users: **1,000** LLM-empowered generative agents initialized from the real dataset.
- **Memory** and **action** modules enable agents to recall past interests and plan future actions (**watch**, **rate**, **evaluate**, **exit**, and **interview**).
- Recommendation environment: Agent4Rec conducts personalized recommendations in a **page-by-page manner** and **pre-implements various recommendation algorithms**.

An Zhang et al. On Generative Agents in Recommendation. SIGIR 2024.

Agents as Users
Agent4Rec

- **Key Observations:**
  - Agents are capable of preserving the user's social attributes and preference.
  - Incorporating agents' rating as augmented data can enhance the recommender's performance.

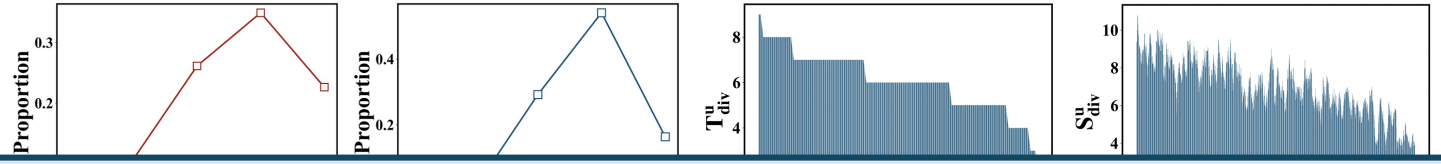
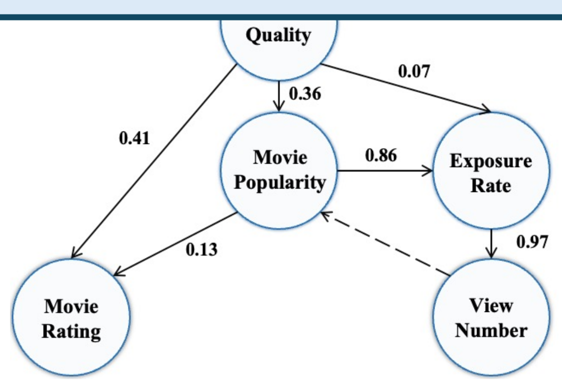


Table 3: Page-by-page recommendation enhancement results over various algorithms.

Offline	MF Recall	MF NDCG	MultVAE Recall	MultVAE NDCG	LightGCN Recall	LightGCN NDCG
Origin	0.1506	0.3561	0.1609	0.3512	0.1757	0.3937

LLM-powered agents are able to generate faithful behaviors.

able to discover **Causal Relations** among movie quality, movie rating, movie popularity, exposure rate, and view number.



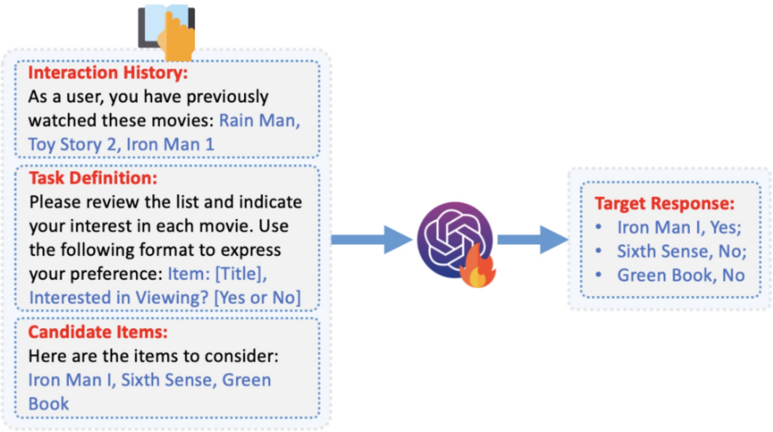
- **Offer a simulation platform to test and fine-tune recommender models.**

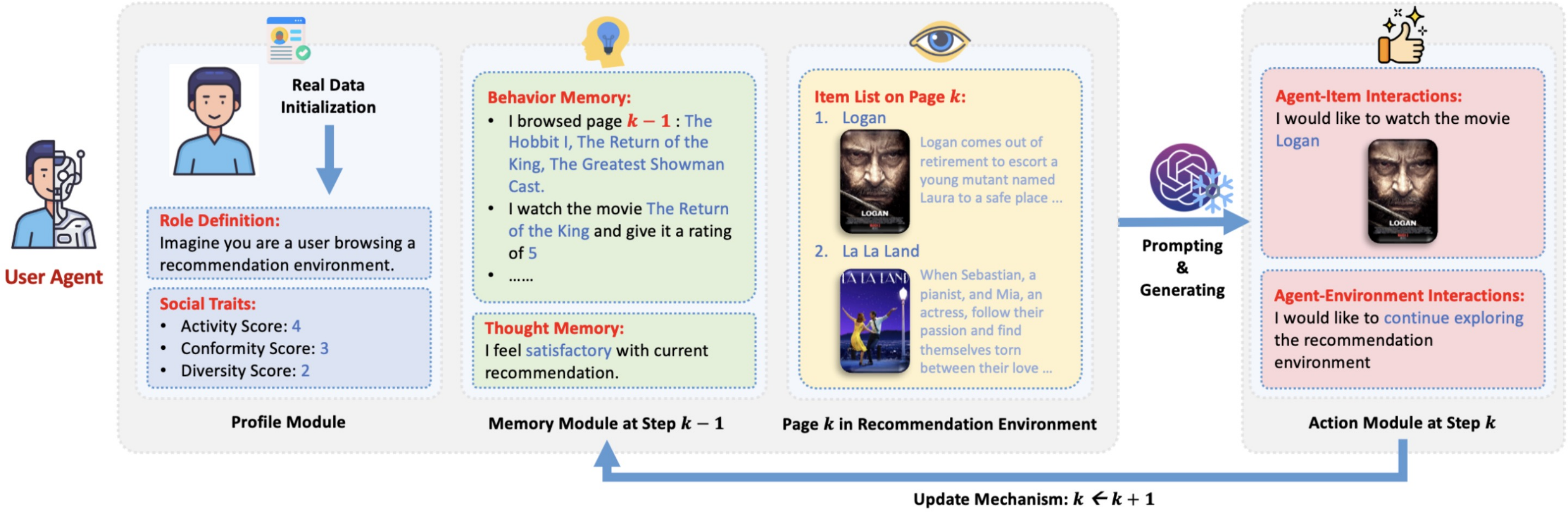
An Zhang et al. On Generative Agents in Recommendation. SIGIR 2024.

Agents as Users
UGen

Agents as Users

- **Key Points :**
  - Can LLM-powered Agents generated behaviors benefit the recommender?
  - Cooperating updated Agent4Rec framework with finetuning GPT-3.5-turbo as a warmup, agents can accurately select their interested items among candidate set.





- Agents have potentials to replace discriminative learning with generative learning paradigms for user modeling in recommendation.
- Conduct extensive experiments on three dataset from different domains (movie, book, game).

Agents as Users
UGen

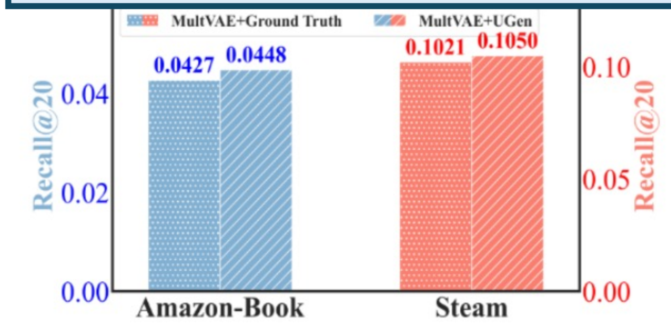
- **Key Observations:**
  - Agents are capable of providing effective behaviors, especially in scenarios with sparse data.

Table 2: Faithfulness Evaluation of Agent's Behavior Alignment with Real User Preferences. Average ground-truth positives are 7.14 (MovieLens), 6.57 (Amazon-Book), and 5.80 (Steam). UGen shows significant improvement with p-value << 0.05.

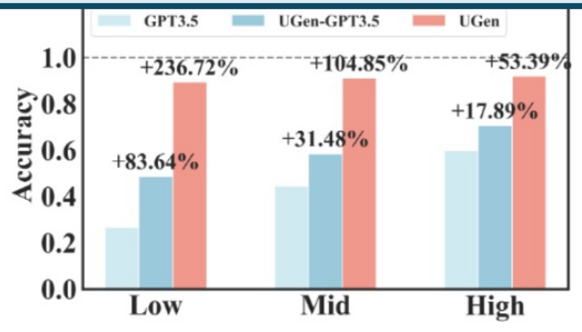
	MovieLens				Amazon-Book				Steam			
	Acc	Pre	Rec	#Select	Acc	Pre	Rec	#Select	Acc	Pre	Rec	#Select
GPT3.5	0.5295	0.4307	0.7369	11.63	0.4202	0.3855	**0.9072**	17.10	0.4350	0.3430	0.9164	16.59
GPT4	0.6930	0.5743	0.6577	7.00	0.7947	0.6500	0.6003	5.16	0.7844	0.5103	0.7072	6.22
RecAgent	0.6168	0.4519	**0.8921**	13.95	0.5411	0.3714	0.8150	14.65	0.4916	0.3485	**0.9389**	15.55
RAH	0.5758	0.4096	0.6383	9.44	0.7253	0.3355	0.3950	7.45	0.6118	0.3874	0.6262	10.37

	MovieLens		Amazon-Book		Steam	
	Recall@20	NDCG@20	Recall@20	NDCG@20	Recall@20	NDCG@20
MF	0.1529	0.3186	0.0257	0.0480	0.0694	0.0567
+ Random	0.1365	0.2913	0.0199	0.0225	0.0526	0.0432
+ GPT3.5	0.1448	0.3089	0.0253	0.0330	0.0732	0.0608
+ RecAgent	0.1400	0.2990	0.0254	0.0317	0.0696	0.0567
+ RAH	0.1363	0.2917	0.0257	0.0370	0.0731	0.0604
+ UGen	**0.1667**	**0.3396**	**0.0413**	**0.0573**	**0.0807**	**0.0659**
Imp.% over MF	*9.03%*	*6.59%*	*60.70%*	*19.38%*	*16.28%*	*16.23%*
+ Random	0.1650	0.3358	0.0257	0.0354	0.0762	0.0604
+ GPT3.5	0.1693	0.3462	0.0408	0.0536	0.0817	0.0694
+ RecAgent	0.1650	0.3393	0.0386	0.0518	0.0802	0.0668
+ RAH	0.1597	0.3340	0.0391	0.0542	0.0867	0.0719
+ UGen	**0.1899**	**0.3722**	**0.0555**	**0.0752**	**0.1140**	**0.0952**
Imp.% over LightGCN	*2.82%*	*2.59%*	*32.14%*	*12.24%*	*28.67%*	*25.76%*

Behaviors generated by LLM-powered agents can benefit recommenders.



(a) Augmented MultVAE



(b) Accuracy on Amazon-Book

Table 4: Human Evaluation on Steam

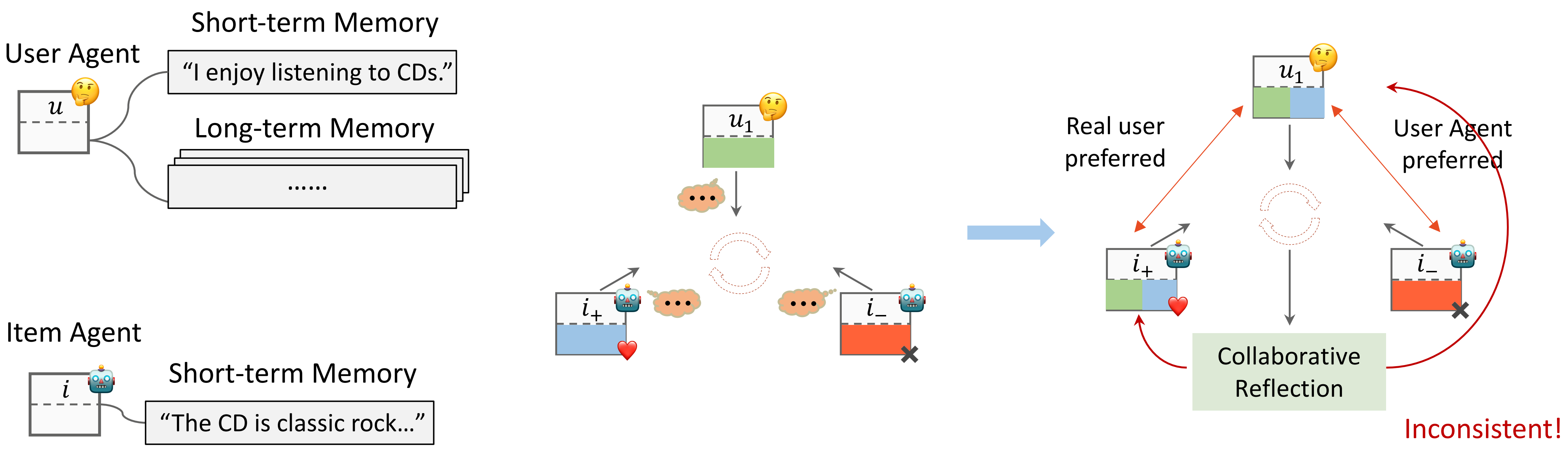
	Random	Pop	MF	MF+Full	MF+Human
Average Rank	4.72	3.22	2.61	2.50	**1.94**

Agents as Users & Items
AgentCF

Agents as Users & Items

❑ **AgentCF: text-based collaborative learning**

- **Key Points:**
  - Can LLM-powered Agent simulate collaborative signals/user-item interactions?



Junjie Zhang et al. AgentCF: Collaborative Learning with Autonomous Language Agents for Recommender Systems. WWW 2024.

Agents as Users & Items
AgentCF

Agents as Users & Items

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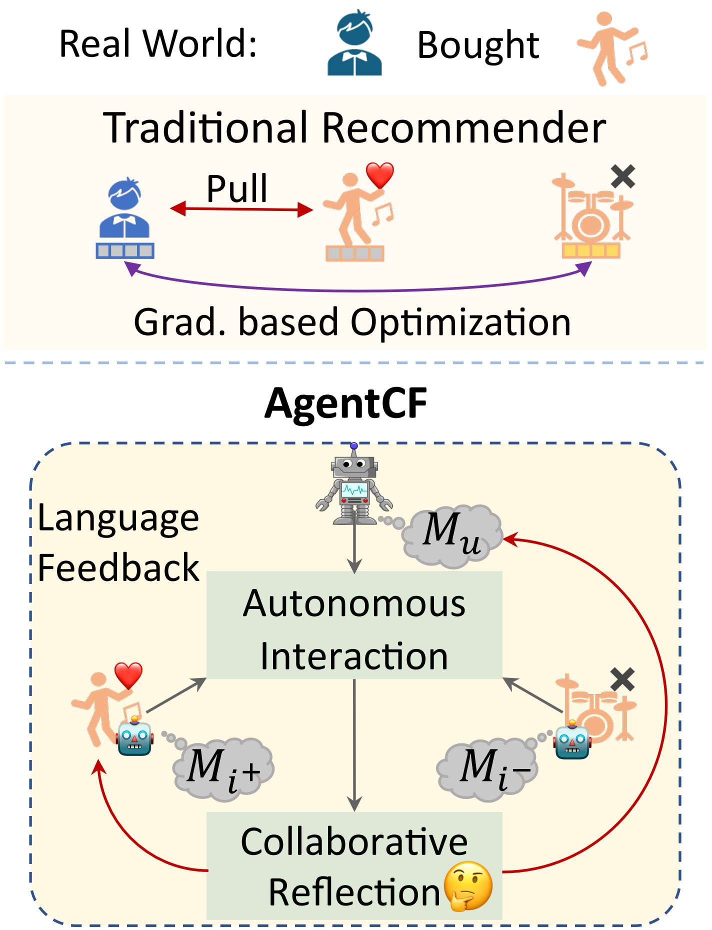
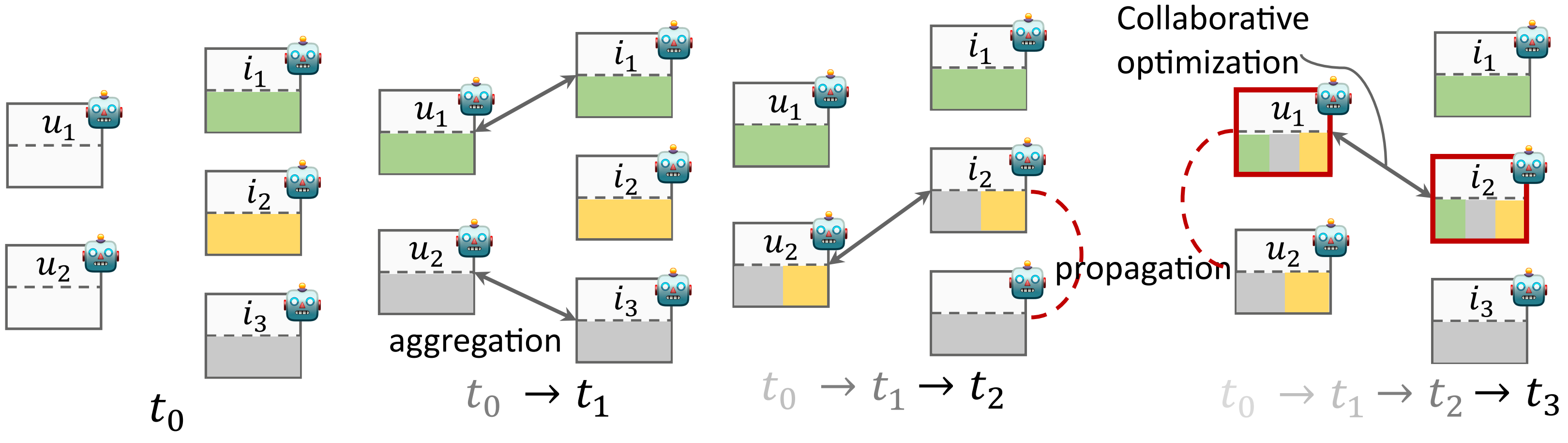


- **Key idea**: Parameter-free text-based collaborative optimization.



Junjie Zhang et al. AgentCF: Collaborative Learning with Autonomous Language Agents for Recommender Systems. WWW 2024.

Agents as Users & Items
AgentCF

- **Key Observations:**
  - Agents are capable of simulating user-item interactions.

Method	CDs_{sparse}			CDs_{dense}			$Office_{sparse}$			$Office_{dense}$		
	N@1	N@5	N@10	N@1	N@5	N@10	N@1	N@5	N@10	N@1	N@5	N@10
BPR_{full}	0.1900	0.4902	0.5619	0.3900	0.6784	0.7089	0.1600	0.3548	0.4983	0.5600	0.7218	0.7625
$SASRec_{full}$	0.3300	0.5680	0.6381	0.5800	0.7618	0.7925	0.2500	0.4106	0.5467	0.4700	0.6226	0.6959
BPR_{sample}	0.1300	0.3597	0.4907	0.1300	0.3485	0.4812	0.0100	0.2709	0.4118	0.1200	0.2705	0.4576
$SASRec_{sample}$	<u>0.1900</u>	0.3948	<u>0.5308</u>	0.1300	0.3151	0.4676	0.0700	0.2775	0.4437	**0.3600**	**0.5027**	**0.6137**

Agents can faithfully simulate user-item interactions.

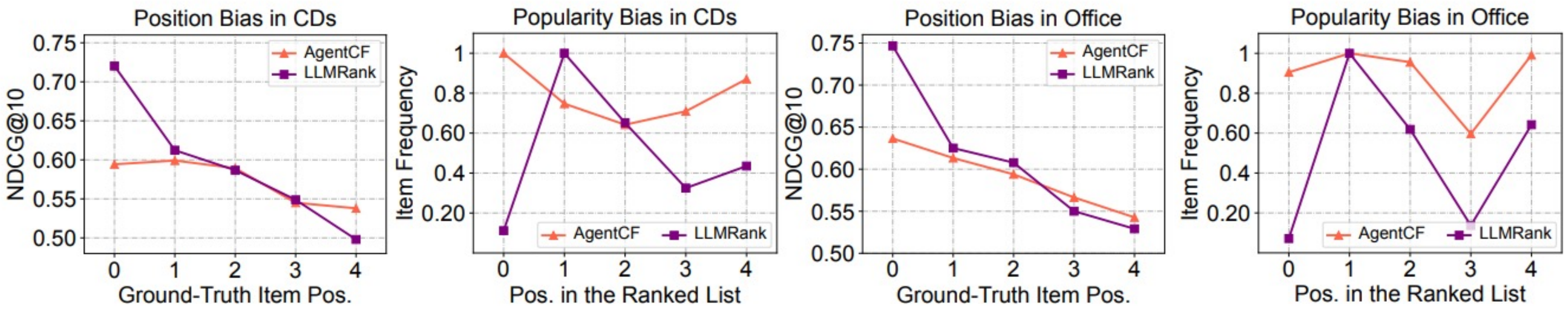
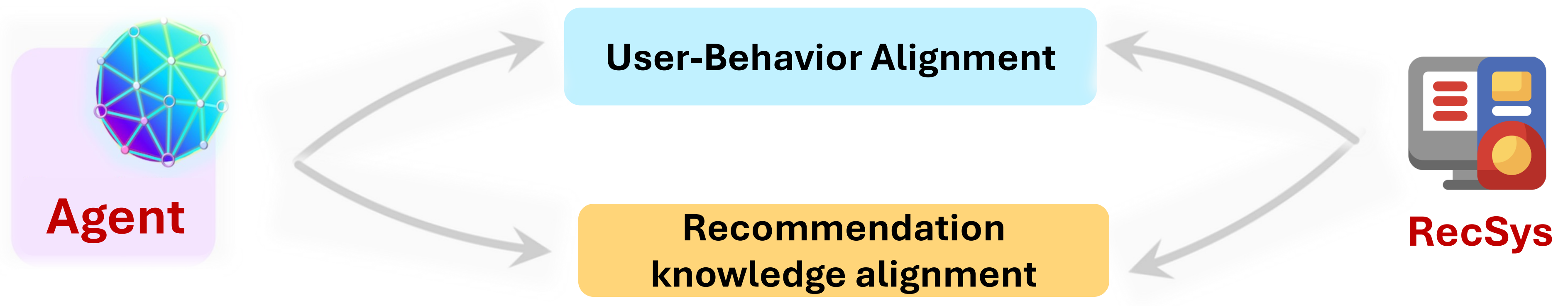


Figure 2: Analysis of whether our approach can simulate personalized agents to mitigate position bias and popularity bias.

LLM-powered Agents in Recommendation



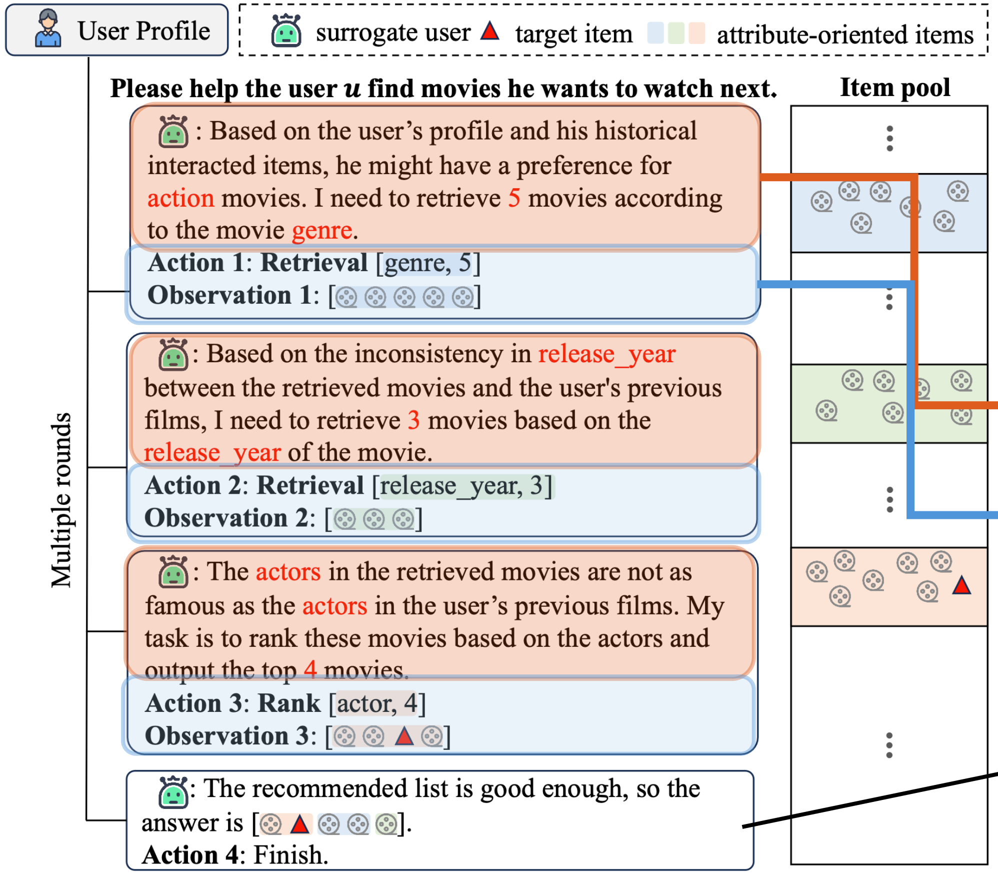
- **LLM-empowered have potentials to solve long-standing problems in recommendation**
  - Can an LLM-powered Agent faithfully simulate **users**?
    - **Agent4Rec, UGen, AgentCF, RecAgent**
  - Can an LLM-powered Agent be a better **recommender** with recommendation-specific knowledge?

Agent as Recommender
ToolRec

Agent as Recommender

❑ **ToolRec: Tool-enhanced LLM-based recommender**

- **Key Points:**
  - Can Agents Utilize External Tools to Enhance Recommendations?



Key Idea:

- **Use LLMs to understand current contexts and preferences, and apply attribute-oriented tools to find suitable items.**

Two stages:

- Learning Preferences: LLM-based surrogate user learns user preferences and makes decisions
- Exploration of Items: uses attribute-oriented tools to explore a wide range of items

❖ Process finishes when the LLM-based surrogate user is satisfied with the item list

Yuyue Zhao et al. Let Me Do It For You: Towards LLM Empowered Recommendation via Tool Learning. SIGIR 2024.

Agent as Recommender
ToolRec

Agent as Recommender

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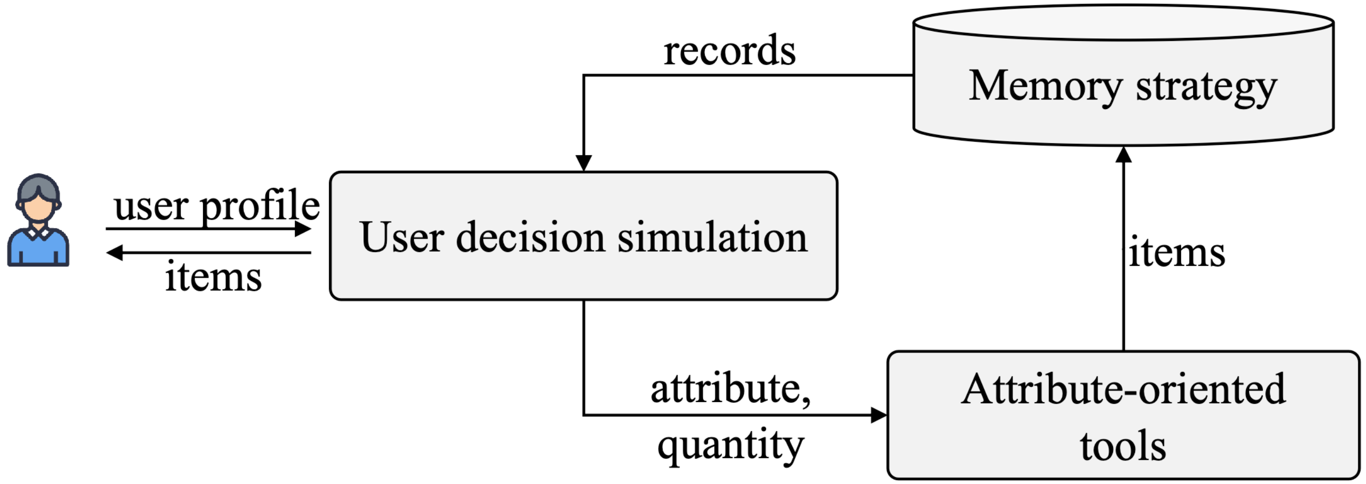


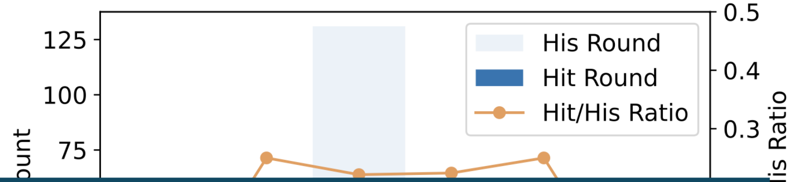
- LLMs as the central controller, simulating the user decision.
- Attribute-oriented Tools: rank tools & retrieval tools.
- Memory strategy can ensure the correctness of generated items and cataloging candidate items.

Yuyue Zhao et al. Let Me Do It For You: Towards LLM Empowered Recommendation via Tool Learning. SIGIR 2024.

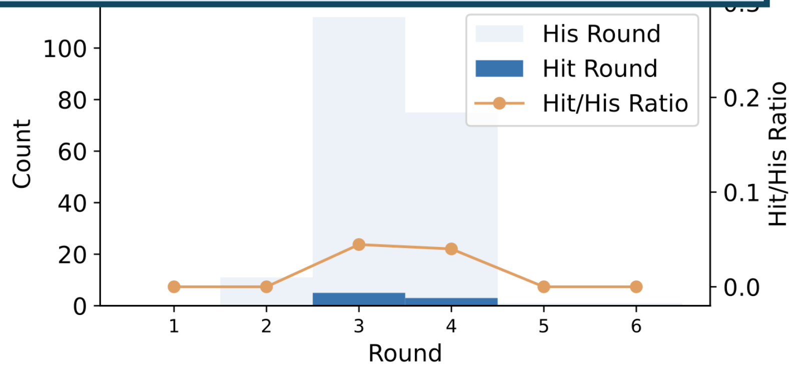
Agent as Recommender
ToolRec

- **Key Observations:**
  - Benefiting from rank tools and retrieval tools, ToolRec excels on the ML-1M and Amazon-Book datasets compared to baseline recommenders, demonstrating that it can better align with the users' intent.

	ML-1M		Amazon-Book		Yelp2018	
	Recall	NDCG	Recall	NDCG	Recall	NDCG
SASRec	0.203±0.047	0.1017±0.016	0.047±0.015	0.0205±0.006	0.030±0.005	0.0165±0.006
ToolRec	**0.215**±0.044	**0.1171**±0.018	**0.053**±0.013	**0.0259**±0.005	0.028±0.003	0.0159±0.001
ToolRec$_B$	0.185±0.018	0.0895±0.002	0.043±0.013	0.0223±0.008	0.025±0.005	0.0136±0.009
Improvement	3.36%	15.10%	14.28%	5.14%	−29.16%	−27.32%



Agents Utilizing External Tools can Enhance Recommendations.



(b) Amazon-Book.

- ToolRec shows subpar performance on the Yelp2018 dataset - local (niche) businesses.
- Most processes conclude in three or four rounds, indicating that the LLM can understand user preferences after a few iterations.

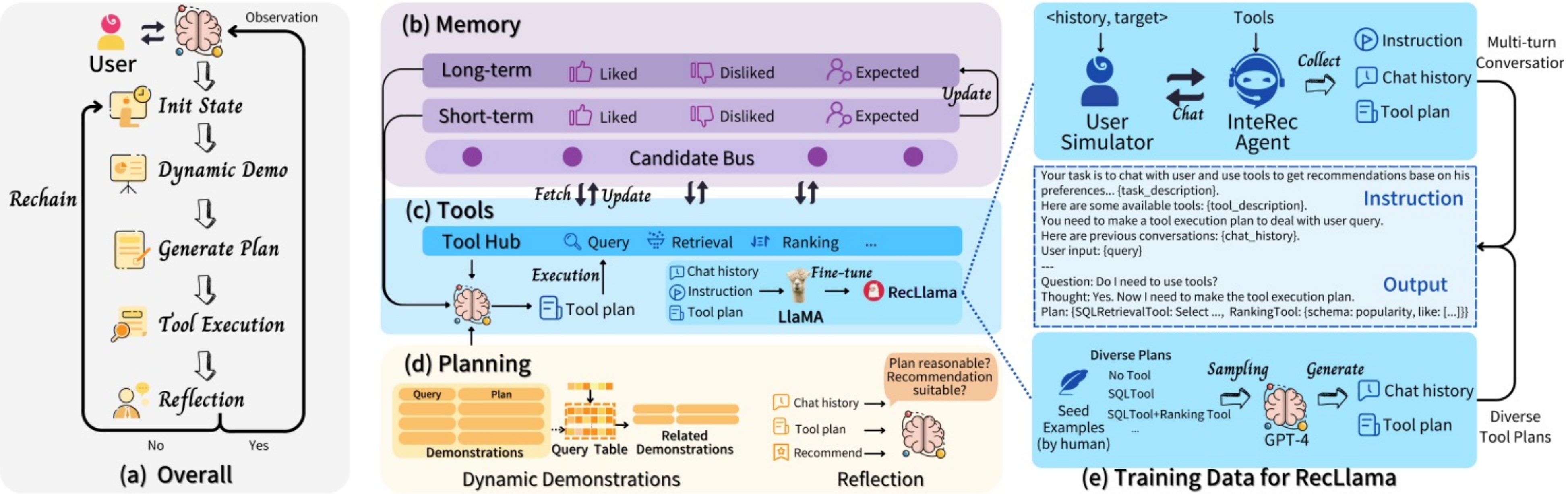
Yuyue Zhao et al. Let Me Do It For You: Towards LLM Empowered Recommendation via Tool Learning. SIGIR 2024.

Agent as Recommender
InteRecAgent

Agent as Recommender

❑ **InteRecAgent: Interactive Recommender.**

- **Key Points:**
  - Agents can create a versatile and interactive recommender system.



- InteRecAgent enables traditional recommender systems, such as those ID-based matrix factorization models, to become interactive systems with a natural language interface.

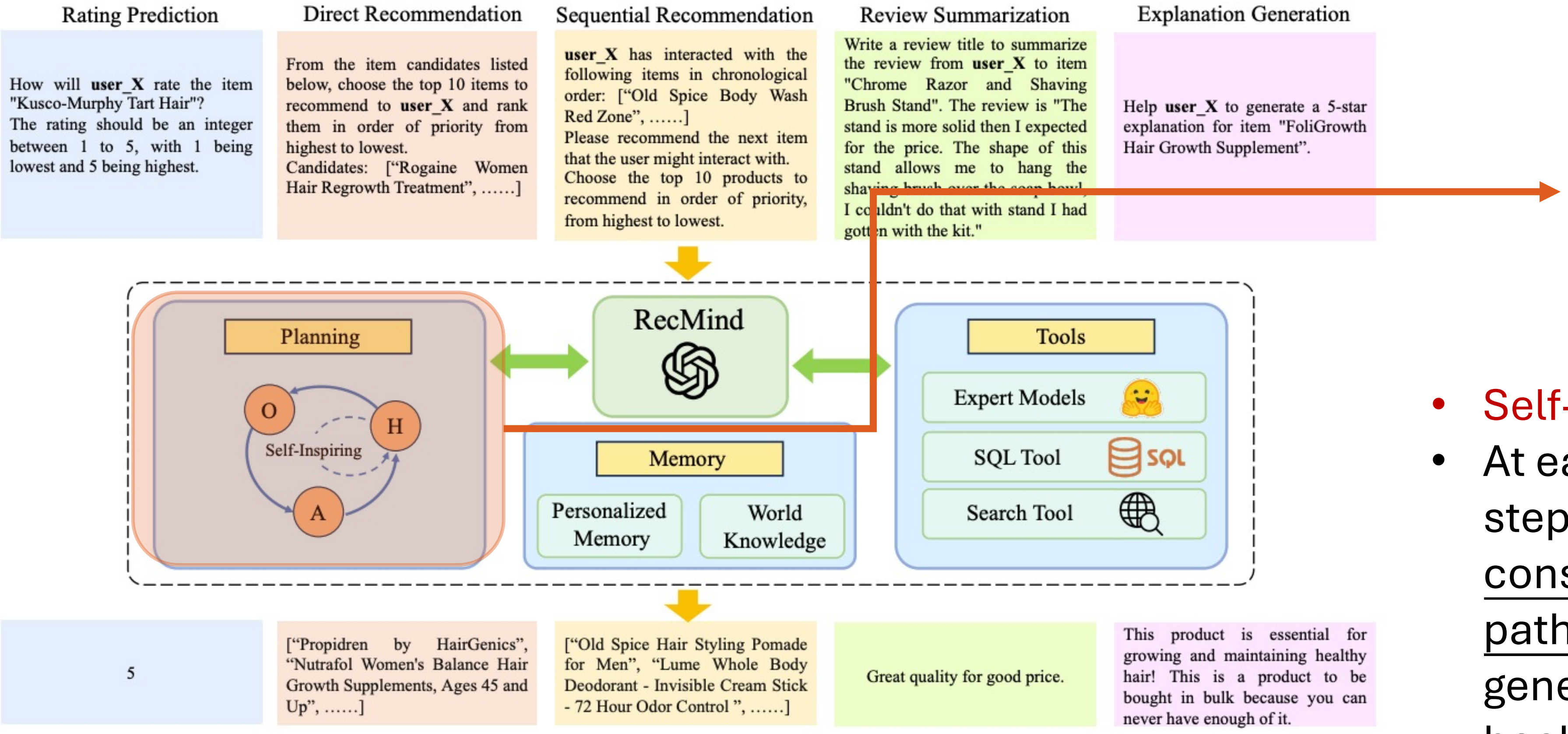
Xu Huang et al. Recommender AI Agent: Integrating Large Language Models for Interactive Recommendations. Arxiv 2023..

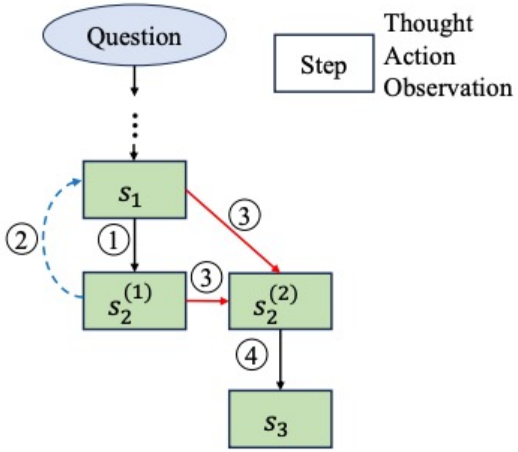
Agent as Recommender
RecMind

Agent as Recommender

- **Key Points:**
  - Can Agents with self-inspiring planning Enhance Recommendations?

RecMind: Recommender agent with Self-Inspiring planning ability





(b) Self-Inspiring

- Self-inspires:
- At each intermediate planning step, the agent "self-inspires" to consider all previously explored paths for the next planning, both generating alternative thoughts and backtracking.

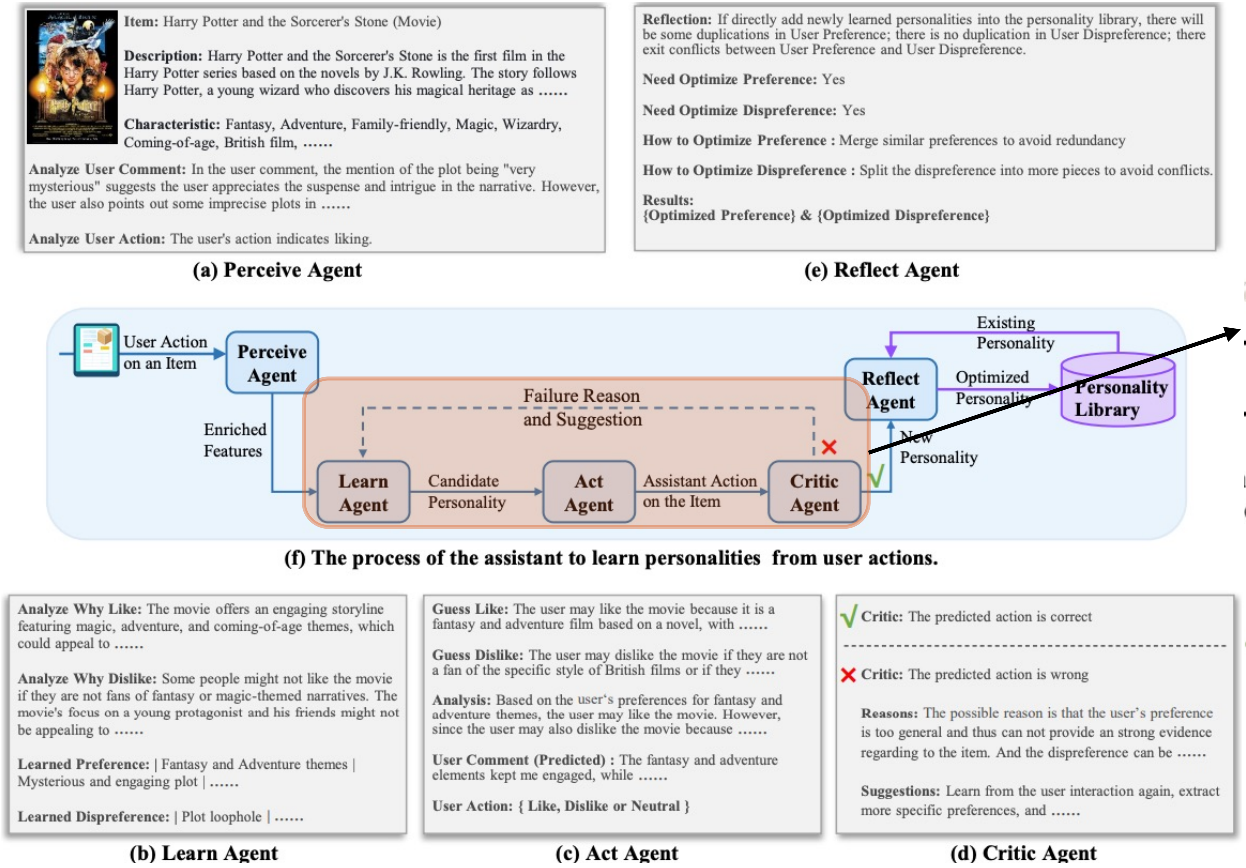
Yancheng Wang et al. "RecMind: Large Language Model Powered Agent For Recommendation.NAACL 2024.

Agent as Recommendation Assistant
RAH

Agent as Rec Assistant

❑ **RAH: Reflection-enhanced user alignment for Rec assistant**

- **Key Points:**
  - Can Agents with Learn-Act-Critic loop comprehend a user's personality from their behaviors?



❖ Learn-Act-Critic Loop:
- Learn Agent collaborates with the Act and Critic Agents in an iterative process to grasp the user's personality.
- Upon receiving user feedback, Learn Agent extracts an initial personality as a candidate.
- Act Agent utilizes this candidate as input to predict the user's actual action.
- The Critic Agent then assesses the accuracy. If incorrect, Learn Agent refines the candidate's personality.

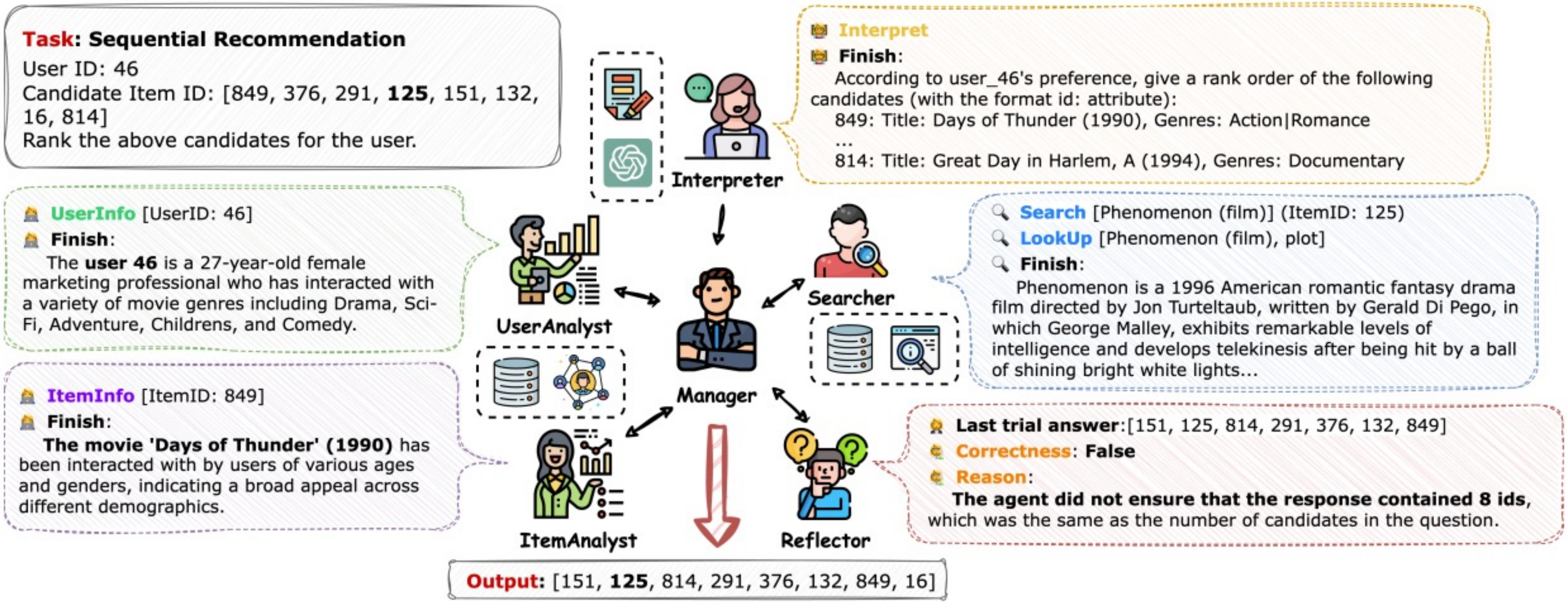
Yubo Shu et al. RAH! RecSys-Assistant-Human: A Human-Centered Recommendation Framework with LLM Agents. Arxiv 2023.

Multi-Agents as Recommender
MACRec

Multi-Agent as Recommender

❑ **MACRec: enhance RecSys through multi-agent collaboration**

- **Key Points:**
  - Multi-agents with different **roles** work collaboratively to tackle a specific recommendation task.



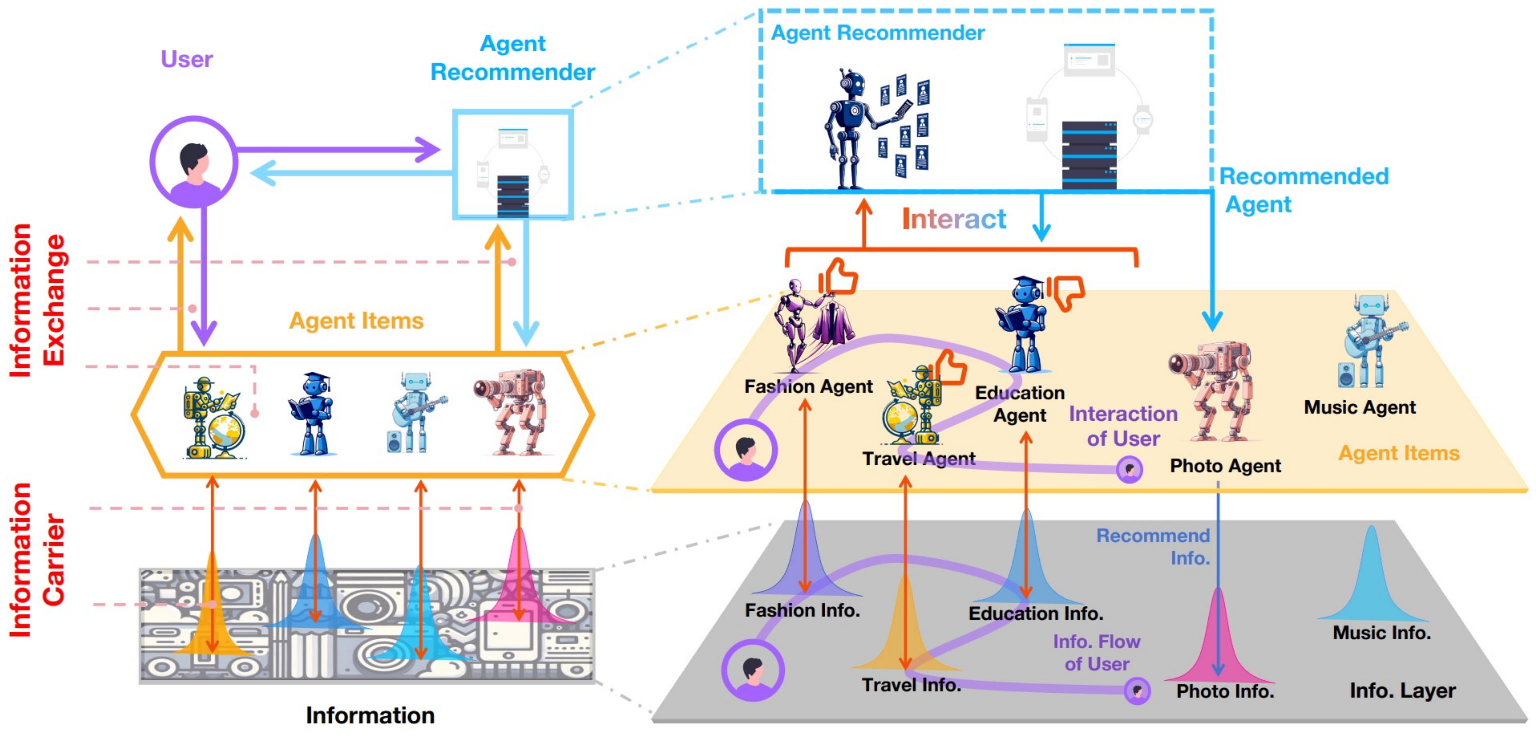
Zhefan Wang et al. Multi-Agent Collaboration Framework for Recommender Systems. Arxiv 2024.

Agent Recommender for Agent Platform
Rec4Agentverse

Agent Recommender

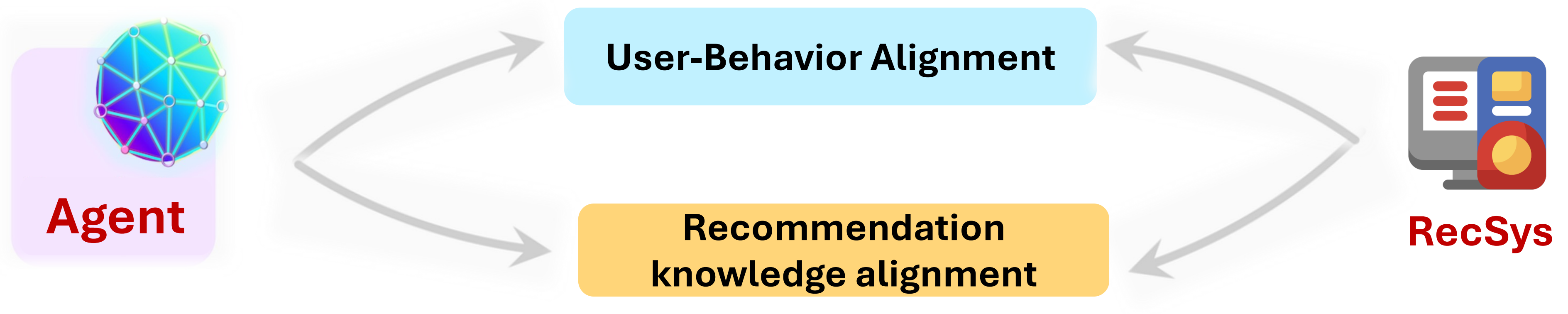
❑ **Rec4Agentverse: Agent recommender for Agent platform**

▪ **Key Points:**
- Treating LLM-based Agents in Agent platform as items in the recommender system.
- **Agent Recommender** is employed to recommend personalized Agent Items for each user.



Jizhi Zhange t al. Prospect Personalized Recommendation on Large Language Model-based Agent Platform. Arxiv 2024.

LLM-powered Agents in Recommendation



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  - Can an LLM-powered Agent be a better **recommender** with recommendation-specific knowledge?
    - **ToolRec, InteRecAgent, RecMind, RAH, MACRec, Rec4Agentverse**

Q&A

Thanks for listening!

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An Zhang's Homepage

Resources