7-2024

Large language model powered agents for information retrieval

An ZHANG

Yang DENG
Singapore Management University, ydeng@smu.edu.sg

Yankai LIN

Xu CHEN

Ji-Rong WEN

See next page for additional authors

Large Language Model Powered Agents for Information Retrieval

An Zhang
National University of Singapore
Singapore
an_zhang@nus.edu.sg

Yang Deng
National University of Singapore
Singapore
ydeng@nus.edu.sg

Yankai Lin
Renmin University of China
Beijing, China
yankailin@ruc.edu.cn

Xu Chen
Renmin University of China
Beijing, China
xu.chen@ruc.edu.cn

Ji-Rong Wen
Renmin University of China
Beijing, China
jrwen@ruc.edu.cn

Tat-Seng Chua
National University of Singapore
Singapore
chuats@comp.nus.edu.sg

ABSTRACT

The vital goal of information retrieval today extends beyond merely connecting users with relevant information they search for. It also aims to enrich the diversity, personalization, and interactivity of that connection, ensuring the information retrieval process is as seamless, beneficial, and supportive as possible in the global digital era. Current information retrieval systems often encounter challenges like a constrained understanding of queries, static and inflexible responses, limited personalization, and restricted interactivity. With the advent of large language models (LLMs), there's a transformative paradigm shift as we integrate LLM-powered agents into these systems. These agents bring forth crucial human capabilities like memory and planning to make them behave like humans in completing various tasks, effectively enhancing user engagement and offering tailored interactions. In this tutorial, we delve into the cutting-edge techniques of LLM-powered agents across various information retrieval fields, such as search engines, social networks, recommender systems, and conversational assistants. We will also explore the prevailing challenges in seamlessly incorporating these agents and hint at prospective research avenues that can revolutionize the way of information retrieval.

CCS CONCEPTS

• **Information systems** → *Social networks*; *Recommender systems*; *Chat*; *Language models.*

KEYWORDS

Large Language Model, Social Network, Recommendation, Conversational Agent

ACM Reference Format:
An Zhang, Yang Deng, Yankai Lin, Xu Chen, Ji-Rong Wen, and Tat-Seng Chua. 2024. Large Language Model Powered Agents for Information Retrieval. In *Proceedings of the 47th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR '24), July 14–18, 2024, Washington, DC, USA.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3626772.3661375

SIGIR '24, July 14–18, 2024, Washington, DC, USA

ACM ISBN 979-8-4007-0431-4/24/07
https://doi.org/10.1145/3626772.3661375

1 MOTIVATION AND OVERVIEW

Information retrieval systems are advancing to accommodate the evolving and complex demands of users. Traditional technologies, characterized by their static and limited capabilities, fall short of fulfilling the user's needs for personalization, interactivity, and diversity. Large language model (LLM) powered agents provide a compelling solution, offering intuitive navigation, personalized content, and real-time assistance, resembling human interactions. With the increasing demand for more sophisticated and intelligent retrieval systems, the exploration of LLM-powered agents becomes crucial, holding the potential to improve the user experience and revolutionize interaction paradigms of information retrieval.

1.1 Background of LLM-powered Agents

Autonomous AI agents have long been regarded as stepping stones towards artificial general intelligence (AGI), with capabilities for self-guided task execution. Traditional approaches employed heuristic policy functions, which often lacked human-level adeptness in open-domain scenarios, largely due to heuristic limitations and constrained training data. Recently, LLMs have shown impressive strides towards human-like intelligence [36]. This advancement has spurred a growing trend in integrating LLMs as central components in developing autonomous AI agents [38, 39, 41, 61].

- **LLM-based Agent's Architecture**. The architectures of existing LLM-based AI agents can be distilled into a consolidated framework, extensively covered in recent survey literature on AI agents [44]. This unified structure comprises four primary modules: profiling, memory, planning, and action. The profiling module determines the agent's role, while the memory and planning modules immerse the agent in a dynamic environment, facilitating recall and strategizing of future action. The action module then converts decisions into concrete outputs. Notably, the profiling module influences both memory and planning modules, which in turn guide the action module.
- **LLM-based Tool Learning**. LLM-based tool learning seeks to meld the prowess of specialized tools and LLMs, enabling LLM-based agents to use external tools, and bringing in better autonomous problem-solving. Recent studies highlight foundation models' adeptness in tool utilization, such as search automation [35, 43, 60], neural model integration [41], computer task execution [27, 52], and embodied robotic learning [2, 25].

1.2 LLM-powered Agents in Social Network

The social network connects different people by allowing them to share opinions and exchange information. Recent years have witnessed many AI techniques to solve social network problems like user connection prediction [54] and social information propagation [5], where the key challenge lies in understanding human intrinsic cognitive processes and behavior patterns. Recently, by learning huge amounts of world knowledge, LLMs have obtained remarkable success in achieving human-level intelligence. This sheds new light on solving social network problems, and several attempts have been made to incorporate LLM-based agents into this field.

- **Social Network Simulation with LLM-based Agents.** Social network simulation is a fundamental problem. If one can accurately simulate a social network, then its underlying mechanism and running rules can be easily understood and utilized. However, due to the intrinsic nature of human minds, it is quite hard to predict how people may behave in social networks. Recently, there have been several attempts [20, 30, 37] to leverage LLM-based agents to solve this problem. The key to these papers is leveraging LLMs as user brains, and designing profile, memory, and planning modules to make LLMs act like humans.
- **Social Network Problem Solving with LLM-based Agents.** Another research line on combining LLM-based agents with social networks is solving specific problems. People have leveraged agents to discover social system dynamics [21], analyze social principles between different agents [3], and so on. This direction is still rapidly growing, and we foresee that there will be much more promising work in the future.

1.3 LLM-powered Agents in Recommendation

Recommender systems play a pivotal role in contemporary information dissemination, actively shaping individual preferences [29]. With the recent advancements in LLMs, LLM-powered agents demonstrate remarkable achievements in autonomous interaction and user preference understanding [33]. This impressive capability can, on one hand, be harnessed to simulate authentic human behavior within recommender systems at both individual and population levels by scaling their deployment. On the other hand, it opens the potential for leveraging LLM-powered agents in the construction of a new paradigm of personalized recommenders [51].

- **User Behavior Simulation with LLM-powered Agents**. Simulating user behavior in recommender systems is a complex endeavor that requires a deep understanding of human preference and behavior patterns [6, 45, 56]. Bridging this gap necessitates not only the incorporation of agent modules that are tailored for recommendation contexts but also accommodation of the multimodal nature of such environments [31, 55]. Hence, agents driven by LLMs must be equipped with and further fine-tuned for multimodal comprehension to approximate the fidelity of real-world user interactions.
- **Recommender Agents**. While contemporary recommender systems are proficient in predicting domain-specific recommendations leveraging user behavioral data, they typically lack capabilities for explaining their recommendations, engaging in user conversations, and integrating rich user data [26]. To create a dynamic and interactive recommender system, LLMs serve as the 'brain', with the recommender model acting as a tool [34, 48]. This research direction is dedicated to developing user-oriented recommender agents for the recommendation ecosystem [42].

1.4 LLM-powered Conversational Agents

LLM-powered conversational agents not only redefine user interaction but also introduce innovative functionalities that push the boundaries of traditional human-computer interactions.

- **LLM-powered Conversational Agents for User Simulation**. Building user simulators [40, 58] has emerged as an effective and efficient technique for evaluating conversational systems, thereby mitigating the high cost of interacting with real users. Inspired by the recent success of leveraging LLMs for role-play scenarios, researchers design LLM-powered conversational agents, which can be flexibly adapted to different dialogue evaluations, including open-domain dialogues [28], task-oriented dialogues [22], and conversational recommendation [46]. Moreover, the profile module can endow conversational agents with the role-playing capability, which contributes to the diversity of simulated users with various personality [59] and user profiles [24].
- **LLM-powered Proactive Conversational Agents**. Despite the exceptional proficiency in context understanding and response generation in various dialogue problems, LLM-based conversational agents typically prioritize accommodating users' intentions as LLMs are trained to passively follow users' instructions. Therefore, LLM-powered conversational agents often face challenges in handling proactive dialogue problems that require the conversational agent to strategically take the initiative to steer the conversation towards an anticipated goal [12]. To this end, recent works investigate prompt-based policy planning methods that prompt an actor LLM to either conduct self-thinking of strategy planning for each turn [13, 57] or generate AI feedback given the whole dialogue history to iteratively improve the dialogue policy planning for proactive dialogues [15, 18, 53].
- **Capability of Multi-turn Instruction Following**. LLM-powered agents [44] showcase exceptional capabilities in performing multi-turn interactions with diverse environments, which contribute to various real-world problem-solving, such as web navigation [9, 19]. Despite the proficiency in executing each individual instruction, the capability of interacting with multi-turn user instructions is crucial for applying LLM-powered agents onto real-world applications [16, 47, 50].

1.5 Open Challenges and Beyond

In the last part, we will discuss the main open challenges in developing LLM-powered agents in information retrieval applications and several potential research directions for future studies.

- **Trustworthy and Reliable Agents**. As LLM-powered agents gain increasing autonomy and responsibility in processing user requests, making decisions, and handling sensitive data, there's a rising concern about their trustworthiness and reliability. While LLM-powered agents are designed to be accurate, hallucination and inconsistency issues [7, 17] can lead to undesired responses. Ensuring that these agents are both trustworthy (data privacy and

ethical considerations [8]) and reliable (consistent and accurate performance) remains a pressing challenge [14].
- **Multi-agent Collaboration and Competition**. As the web ecosystem grows in complexity, there is a foreseeable future where multiple LLM-powered agents will need to interact with each other, either collaboratively to achieve common goals or competitively. Designing agents that can effectively collaborate requires addressing challenges in communication [49], shared knowledge bases [61], and synchronizing actions in real-time [1]. On the other hand, competitive scenarios [18] necessitate agents that can strategize, negotiate, and adapt to dynamic conditions.

2 OBJECTIVES

The main objectives of this tutorial are threefold:

- This tutorial presents a comprehensive and diverse overview of the cutting-edge designs of LLM-powered agents in various IR applications. The discussed approaches are problem-driven and language-agnostic, which means that the techniques are also not limited to a certain type of dialogue and can be generalized to diverse IR applications.
- This tutorial discusses open challenges for LLM-powered agents in solving various IR problems. LLMs have showcased exceptional capabilities in behaving and thinking as human beings. We provide a new perspective to facilitate more potential directions for future research into IR applications.
- This tutorial provides the opportunity to arouse discussions on LLM-powered agents from not only the IR perspective but also other perspectives, including human-computer interaction, computational social science, etc.

3 RELEVANCE TO INFORMATION RETRIEVAL

The autonomous AI agent powered by LLMs is a trending topic across various information retrieval applications, such as search engines [43, 60], recommendation [26, 45, 55], and conversational systems [15, 18]. This topic receives notably increasing attention from both academia and industry. In academia, the SIGIR conference this year notably emphasizes an especially interest in *information retrieval or recommender systems with large language models (LLMs)*. In industry, the recent period has witnessed numerous successful deployments of LLM-integrated information retrieval applications. For instance, Microsoft unveiled an updated version of Bing that incorporates ChatGPT. Furthermore, a series of tutorials focusing on the application of LLMs in information retrieval have been presented at top-tier conferences, including but not limited to

- *Tutorial on Large Language Models for Recommendation* at RecSys 2023 [23]
- *Proactive Conversational Agents in the Post-ChatGPT World* at SIGIR 2023 [32]
- *Goal Awareness for Conversational AI: Proactivity, Non-collaborativity, and Beyond* at ACL 2023 [10]
- *Rethinking Conversational Agents in the Era of LLMs: Proactivity, Non-collaborativity, and Beyond* at SIGIR-AP 2023 [11]
- *Large Language Models for Recommendation: Progresses and Future Directions* at SIGIR-AP 2023 [4]

However, these tutorials mainly introduce advanced designs for building specific information retrieval applications with the assistance of LLMs. In our tutorial, we aim to elaborate a comprehensive introduction to cutting-edge research on LLM-powered agents across multiple important information retrieval applications.

4 DETAILED SCHEDULE

The following summarizes the detailed schedule of the tutorial:

(1) Introduction [10 min]
(2) Background of LLM-powered Agents [35 min]
  (a) Agent Architecture
  (b) Tool Learning
  (c) Search Agents
(3) LLM-powered Agents in Social Network [35 min]
  (a) Social Network Simulation with LLM-based Agents
  (b) Social Network Problem Solving with LLM-based Agents
(4) LLM-powered Agents in Recommendation [35 min]
  (a) User Behavior Simulation with LLM-powered Agents
  (b) Recommender Agents
(5) LLM-powered Conversational Agents [35 min]
  (a) LLMs for User Simulation in Conversations
  (b) Proactive Conversational Agents
  (c) Multi-turn Instruction Following of Conversational Agents
(6) Open Challenges and Beyond [20 min]
  (a) Trustworthy and Reliable Agents
  (b) Multi-agent Collaboration and Competition
  (c) Human-Agent Interaction
(7) Summary and Outlook [10 min]

5 SUPPORTING MATERIALS

(1) **Slides** will be made publicly available; and (2) **A survey** [44] is accompanied with this tutorial.

REFERENCES

[1] Saaket Agashe, Yue Fan, and Xin Eric Wang. 2023. Evaluating Multi-Agent Coordination Abilities in Large Language Models. *CoRR* (2023).
[2] Michael Ahn, Anthony Brohan, Noah Brown, Yevgen Chebotar, Omar Cortes, Byron David, Chelsea Finn, Keerthana Gopalakrishnan, Karol Hausman, Alex Herzog, et al. 2022. Do as i can, not as i say: Grounding language in robotic affordances. *ArXiv preprint* abs/2204.01691 (2022).
[3] Jitao Bai, Simiao Zhang, and Zhonghao Chen. 2023. Is There Any Social Principle for LLM-Based Agents? *arXiv preprint arXiv:2308.11136* (2023).
[4] Keqin Bao, Jizhi Zhang, Yang Zhang, Wang Wenjie, Fuli Feng, and Xiangnan He. 2023. Large Language Models for Recommendation: Progresses and Future Directions. In *Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region, SIGIR-AP 2023*. ACM, 306–309.
[5] Meeyoung Cha, Alan Mislove, and Krishna P Gummadi. 2009. A measurement-driven analysis of information propagation in the flickr social network. In *WWW 2009*.
[6] Jin Chen, Zheng Liu, Xu Huang, Chenwang Wu, Qi Liu, Gangwei Jiang, Yuanhao Pu, Yuxuan Lei, Xiaolong Chen, Xingmei Wang, Defu Lian, and Enhong Chen. 2023. When Large Language Models Meet Personalization: Perspectives of Challenges and Opportunities. *CoRR* (2023).
[7] Liang Chen, Yang Deng, Yatao Bian, Zeyu Qin, Bingzhe Wu, Tat-Seng Chua, and Kam-Fai Wong. 2023. Beyond Factuality: A Comprehensive Evaluation of Large Language Models as Knowledge Generators. *CoRR* (2023).
[8] Boyi Deng, Wenjie Wang, Fuli Feng, Yang Deng, Qifan Wang, and Xiangnan He. 2023. Attack Prompt Generation for Red Teaming and Defending Large Language Models. In *Findings of ACL: EMNLP 2023*. 2176–2189.
[9] Xiang Deng, Yu Gu, Boyuan Zheng, Shijie Chen, Samuel Stevens, Boshi Wang, Huan Sun, and Yu Su. 2023. Mind2Web: Towards a Generalist Agent for the Web. In *NeurIPS 2023*.
[10] Yang Deng, Wenqiang Lei, Minlie Huang, and Tat-Seng Chua. 2023. Goal Awareness for Conversational AI: Proactivity, Non-collaborativity, and Beyond. In *ACL 2023*. 1–10.

[11] Yang Deng, Wenqiang Lei, Minlie Huang, and Tat-Seng Chua. 2023. Rethinking Conversational Agents in the Era of LLMs: Proactivity, Non-collaborativity, and Beyond. In *Annual International ACM SIGIR Conference on Research and Development in Information Retrieval in the Asia Pacific Region, SIGIR-AP 2023*. ACM, 298–301.

[12] Yang Deng, Wenqiang Lei, Wai Lam, and Tat-Seng Chua. 2023. A Survey on Proactive Dialogue Systems: Problems, Methods, and Prospects. In *IJCAI 2023*.

[13] Yang Deng, Lizi Liao, Liang Chen, Hongru Wang, Wenqiang Lei, and Tat-Seng Chua. 2023. Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration. In *Findings of ACL: EMNLP 2023*. 10602–10621.

[14] Yang Deng, Lizi Liao, Zhonghua Zheng, Grace Hui Yang, and Tat-Seng Chua. 2024. Towards Human-centered Proactive Conversational Agents. *arXiv preprint arXiv:2404.12670* (2024).

[15] Yang Deng, Wenxuan Zhang, Wai Lam, See-Kiong Ng, and Tat-Seng Chua. 2024. Plug-and-Play Policy Planner for Large Language Model Powered Dialogue Agents. In *ICLR 2024*.

[16] Yang Deng, Xuan Zhang, Wenxuan Zhang, Yifei Yuan, See-Kiong Ng, and Tat-Seng Chua. 2024. On the Multi-turn Instruction Following for Conversational Web Agents.

[17] Yang Deng, Yong Zhao, Moxin Li, See-Kiong Ng, and Tat-Seng Chua. 2024. Gotcha! Don't trick me with unanswerable questions! Self-aligning Large Language Models for Responding to Unknown Questions. *CoRR* abs/2402.15062 (2024).

[18] Yao Fu, Hao Peng, Tushar Khot, and Mirella Lapata. 2023. Improving Language Model Negotiation with Self-Play and In-Context Learning from AI Feedback. *CoRR* abs/2305.10142 (2023).

[19] Hiroki Furuta, Ofir Nachum, Kuang-Huei Lee, Yutaka Matsuo, Shixiang Shane Gu, and Izzeddin Gur. 2023. Multimodal Web Navigation with Instruction-Finetuned Foundation Models. *CoRR* (2023).

[20] Chen Gao, Xiaochong Lan, Zhihong Lu, Jinzhu Mao, Jinghua Piao, Huandong Wang, Depeng Jin, and Yong Li. 2023. S3: Social-network Simulation System with Large Language Model-Empowered Agents. *arXiv preprint arXiv:2307.14984* (2023).

[21] Navid Ghaffarzadegan, Aritra Majumdar, Ross Williams, and Niyousha Hosseinichimeh. 2023. Generative Agent-Based Modeling: Unveiling Social System Dynamics through Coupling Mechanistic Models with Generative Artificial Intelligence. *arXiv preprint arXiv:2309.11456* (2023).

[22] Zhiyuan Hu, Yue Feng, Anh Tuan Luu, Bryan Hooi, and Aldo Lipani. 2023. Unlocking the Potential of User Feedback: Leveraging Large Language Model as User Simulator to Enhance Dialogue System. In *CIKM 2023*.

[23] Wenyue Hua, Lei Li, Shuyuan Xu, Li Chen, and Yongfeng Zhang. 2023. Tutorial on Large Language Models for Recommendation. In *RecSys 2023*.

[24] Chen Huang, Peixin Qin, Yang Deng, Wenqiang Lei, Jiancheng Lv, and Tat-Seng Chua. 2024. Concept–An Evaluation Protocol on Conversation Recommender Systems with System-and User-centric Factors. *arXiv preprint arXiv:2404.03304* (2024).

[25] Wenlong Huang, Pieter Abbeel, Deepak Pathak, and Igor Mordatch. 2022. Language Models as Zero-Shot Planners: Extracting Actionable Knowledge for Embodied Agents. In *ICML 2022*.

[26] Xu Huang, Jianxun Lian, Yuxuan Lei, Jing Yao, Defu Lian, and Xing Xie. 2023. Recommender AI Agent: Integrating Large Language Models for Interactive Recommendations.

[27] Geunwoo Kim, Pierre Baldi, and Stephen McAleer. 2023. Language Models can Solve Computer Tasks.

[28] Chuyi Kong, Yaxin Fan, Xiang Wan, Feng Jiang, and Benyou Wang. 2023. Large Language Model as a User Simulator. *CoRR* abs/2308.11534 (2023).

[29] Yehuda Koren, Steffen Rendle, and Robert M. Bell. 2022. Advances in Collaborative Filtering. In *Recommender Systems Handbook*. Springer US, 91–142.

[30] Xiaochong Lan, Chen Gao, Depeng Jin, and Yong Li. 2023. Stance Detection with Collaborative Role-Infused LLM-Based Agents. *arXiv preprint arXiv:2310.10467* (2023).

[31] Yuan Li, Yixuan Zhang, and Lichao Sun. 2023. MetaAgents: Simulating Interactions of Human Behaviors for LLM-based Task-oriented Coordination via Collaborative Generative Agents.

[32] Lizi Liao, Grace Hui Yang, and Chirag Shah. 2023. Proactive Conversational Agents in the Post-ChatGPT World. In *SIGIR 2023*.

[33] Jianghao Lin, Xinyi Dai, Yunjia Xi, Weiwen Liu, Bo Chen, Xiangyang Li, Chenxu Zhu, Huifeng Guo, Yong Yu, Ruiming Tang, and Weinan Zhang. 2023. How Can Recommender Systems Benefit from Large Language Models: A Survey.

[34] Jianghao Lin, Rong Shan, Chenxu Zhu, Kounianhua Du, Bo Chen, Shigang Quan, Ruiming Tang, Yong Yu, and Weinan Zhang. 2023. ReLLa: Retrieval-enhanced Large Language Models for Lifelong Sequential Behavior Comprehension in Recommendation.

[35] Reiichiro Nakano, Jacob Hilton, Suchir Balaji, Jeff Wu, Long Ouyang, Christina Kim, Christopher Hesse, Shantanu Jain, Vineet Kosaraju, William Saunders, et al. 2021. WebGPT: Browser-assisted question-answering with human feedback. *ArXiv preprint* abs/2112.09332 (2021).

[36] OpenAI. 2023. GPT-4 Technical Report. arXiv:2303.08774

[37] Joon Sung Park, Joseph C O'Brien, Carrie J Cai, Meredith Ringel Morris, Percy Liang, and Michael S Bernstein. 2023. Generative agents: Interactive simulacra of human behavior. *arXiv preprint arXiv:2304.03442* (2023).

[38] Yujia Qin, Shengding Hu, Yankai Lin, Weize Chen, Ning Ding, Ganqu Cui, Zheni Zeng, Yufei Huang, Chaojun Xiao, Chi Han, et al. 2023. Tool learning with foundation models. *arXiv preprint arXiv:2304.08354* (2023).

[39] Yujia Qin, Shihao Liang, Yining Ye, Kunlun Zhu, Lan Yan, Yaxi Lu, Yankai Lin, Xin Cong, Xiangru Tang, Bill Qian, et al. 2023. ToolLLM: Facilitating Large Language Models to Master 16000+ Real-world APIs. (2023).

[40] Ivan Sekulic, Mohammad Aliannejadi, and Fabio Crestani. 2022. Evaluating Mixed-initiative Conversational Search Systems via User Simulation. In *WSDM 2022*.

[41] Yongliang Shen, Kaitao Song, Xu Tan, Dongsheng Li, Weiming Lu, and Yueting Zhuang. 2023. Hugginggpt: Solving ai tasks with chatgpt and its friends in huggingface. *arXiv preprint arXiv:2303.17580* (2023).

[42] Yubo Shu, Haonan Zhang, Hansu Gu, Peng Zhang, Tun Lu, Dongsheng Li, and Ning Gu. 2023. RAH! RecSys-Assistant-Human: A Human-Centered Recommendation Framework with LLM Agents.

[43] Weiwei Sun, Lingyong Yan, Xinyu Ma, Shuaiqiang Wang, Pengjie Ren, Zhumin Chen, Dawei Yin, and Zhaochun Ren. 2023. Is ChatGPT Good at Search? Investigating Large Language Models as Re-Ranking Agents. In *EMNLP 2023*.

[44] Lei Wang, Chen Ma, Xueyang Feng, Zeyu Zhang, Hao Yang, Jingsen Zhang, Zhiyuan Chen, Jiakai Tang, Xu Chen, Yankai Lin, et al. 2023. A survey on large language model based autonomous agents. *arXiv preprint arXiv:2308.11432* (2023).

[45] Lei Wang, Jingsen Zhang, Xu Chen, Yankai Lin, Ruihua Song, Wayne Xin Zhao, and Ji-Rong Wen. 2023. RecAgent: A Novel Simulation Paradigm for Recommender Systems. *arXiv* (2023).

[46] Xiaolei Wang, Xinyu Tang, Wayne Xin Zhao, Jingyuan Wang, and Ji-Rong Wen. 2023. Rethinking the Evaluation for Conversational Recommendation in the Era of Large Language Models. In *EMNLP 2023*.

[47] Xingyao Wang, Zihan Wang, Jiateng Liu, Yangyi Chen, Lifan Yuan, Hao Peng, and Heng Ji. 2024. MINT: Evaluating LLMs in Multi-turn Interaction with Tools and Language Feedback. In *ICLR 2024*.

[48] Yancheng Wang, Ziyan Jiang, Zheng Chen, Fan Yang, Yingxue Zhou, Eunah Cho, Xing Fan, Xiaojiang Huang, Yanbin Lu, and Yingzhen Yang. 2023. RecMind: Large Language Model Powered Agent For Recommendation.

[49] Zhenhailong Wang, Shaoguang Mao, Wenshan Wu, Tao Ge, Furu Wei, and Heng Ji. 2023. Unleashing Cognitive Synergy in Large Language Models: A Task-Solving Agent through Multi-Persona Self-Collaboration. *CoRR* (2023).

[50] Tianbao Xie, Fan Zhou, Zhoujun Cheng, Peng Shi, Luoxuan Weng, Yitao Liu, Toh Jing Hua, Junning Zhao, Qian Liu, Che Liu, Leo Z. Liu, Yiheng Xu, Hongjin Su, Dongchan Shin, Caiming Xiong, and Tao Yu. 2023. OpenAgents: An Open Platform for Language Agents in the Wild. *CoRR* abs/2310.10634 (2023).

[51] Zhengyi Yang, Jiancan Wu, Yanchen Luo, Jizhi Zhang, Yancheng Yuan, An Zhang, Xiang Wang, and Xiangnan He. 2023. Large Language Model Can Interpret Latent Space of Sequential Recommender.

[52] Shunyu Yao, Howard Chen, John Yang, and Karthik Narasimhan. 2022. Webshop: Towards scalable real-world web interaction with grounded language agents. *ArXiv preprint* abs/2207.01206 (2022).

[53] Xiao Yu, Maximillian Chen, and Zhou Yu. 2023. Prompt-Based Monte-Carlo Tree Search for Goal-Oriented Dialogue Policy Planning. In *EMNLP 2023*.

[54] Herman Yuliansyah, Zulaiha Ali Othman, and Azuraliza Abu Bakar. 2020. Taxonomy of link prediction for social network analysis: a review. *IEEE Access* 8 (2020), 183470–183487.

[55] An Zhang, Leheng Sheng, Yuxin Chen, Hao Li, Yang Deng, Xiang Wang, and Tat-Seng Chua. 2024. On Generative Agents in Recommendation. In *WWW*.

[56] Junjie Zhang, Yupeng Hou, Ruobing Xie, Wenqi Sun, Julian McAuley, Wayne Xin Zhao, Leyu Lin, and Ji-Rong Wen. 2023. AgentCF: Collaborative Learning with Autonomous Language Agents for Recommender Systems.

[57] Qiang Zhang, Jason Naradowsky, and Yusuke Miyao. 2023. Ask an Expert: Leveraging Language Models to Improve Strategic Reasoning in Goal-Oriented Dialogue Models. In *Findings of ACL: ACL 2023*.

[58] Shuo Zhang and Krisztian Balog. 2020. Evaluating Conversational Recommender Systems via User Simulation. In *KDD 2020*.

[59] Tong Zhang, Chen Huang, Yang Deng, Hongru Liang, Jia Liu, Zujie Wen, Wenqiang Lei, and Tat-Seng Chua. 2024. Strength Lies in Differences! Towards Effective Non-collaborative Dialogues via Tailored Strategy Planning. *CoRR* abs/2403.06769 (2024).

[60] Yujia Zhou, Qiannan Zhu, Jiajie Jin, and Zhicheng Dou. 2024. Cognitive Personalized Search Integrating Large Language Models with an Efficient Memory Mechanism. WWW 2024.

[61] Xizhou Zhu, Yuntao Chen, Hao Tian, Chenxin Tao, Weijie Su, Chenyu Yang, Gao Huang, Bin Li, Lewei Lu, Xiaogang Wang, Yu Qiao, Zhaoxiang Zhang, and Jifeng Dai. 2023. Ghost in the Minecraft: Generally Capable Agents for Open-World Environments via Large Language Models with Text-based Knowledge and Memory. *CoRR* (2023).