# Large Language Model Powered Agents for Information Retrieval

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## 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

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## 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.

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