Current Trend of AI agent

in the field of Recommendtion system

References

- https://arxiv.org/pdf/2303.14524
- https://arxiv.org/pdf/2502.10050

기존 추천 시스템의 한계

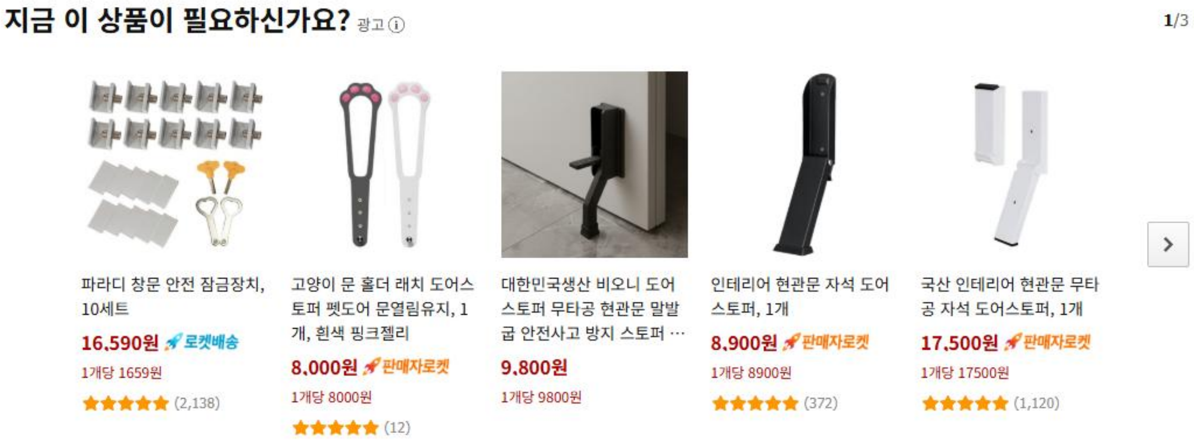
구분	한계 내용	설명
① 수동적(passive) 추천	사용자의 “요구”나 “의도”를 직접 이해하지 못함	사용자가 클릭·시청해야만 추천이 바뀜. “왜 이걸 추천하는가?”에 대한 맥락 이해가 없음.
② 콜드 스타트(cold start)	신규 사용자/아이템에 대한 정보 부족	처음 들어온 유저나 신상품에는 추천 품질이 급격히 낮음.
③ 맥락(context) 부족	시간, 장소, 감정, 상황 등 고려 불가	“밤 11시엔 조용한 음악”, “출근길엔 뉴스” 같은 컨텍스트 반영이 어려움.
④ 짧은 기억(short-term memory)	세션 기반 or 최근 로그 위주	장기적 선호(“예전부터 좋아하던 감독”)가 무시됨. 장기/단기 기억 통합이 안 됨.
⑤ 일방향적 상호작용	추천 → 사용자 선택(끝)	사용자가 “이건 별로야”, “이런 느낌 좋아” 등의 피드백을 실시간 반영하기 어려움.
⑥ 설명 불가능(black box)	왜 이 추천이 나왔는지 설명 어려움	사용자 신뢰(trust)나 규제 측면(예: EU AI 법)에서 문제가 됨.
⑦ 다양성 부족 (diversity issue)	인기 아이템만 계속 추천됨	

-chatgpt

결국..

여러가지 이유를 종합하면 , 사용자에 따른 개인화가 부족하다는 결론이 나온다.

➔추천시스템의 결과가 사용자의 니즈를 만족시키지 못한다.



<- 필요없는 아이템들.

한계 보완 - A Survey on LLM-powered Agents for Recommender Systems

- https://arxiv.org/pdf/2502.10050

에서는 LLM 과 Recommender system 을 결합한다.

Recommender systems are essential components of many online platforms, yet traditional approaches still struggle with understanding complex user preferences and providing explainable recommendations. The emergence of Large Language Model (LLM)-powered agents offers a promising approach by enabling natural language interactions and interpretable reasoning, potentially transforming research in recommender systems. This survey pro-

2.2 LLM as Agent

Large Language Model (LLM) as an agent is an emerging research direction that has garnered significant attention [Park *et al.*, 2023]. By transcending the traditional static prompt-response paradigm, it establishes a dynamic decision-making framework [Patil *et al.*, 2023] capable of systematically decomposing complex tasks into manageable components. A

한계 보완 - A Survey on LLM-powered Agents for Recommender Systems

기존의 방식 : user space U = [u1, u2, ..., um], an item space I = [i1, i2, ..., in], and their interaction matrix $D \in R^{m \times n}$. The fundamental goal is to learn a preference function $p : U \times I \rightarrow R$ that predicts user preferences

(유저 행렬) 각 아이템에 대한 유저의 선호도를 나타냄 -> 여기서 추천시스템의 목표는 아직 드러나지 않은 선호도 중 높은것을 찾아서 제공하는 것

(아이템 행렬) 각 아이템의 정보가 담겨 있음 (ex 영화의 장르 , 평점 평균 등)

(상호작용 행렬) 각 아이템을 유저가 구매하였는가를 나타내는 행렬

앞의 두 행렬의 변화가 상호작용 행렬의 결과에 맞도록 하는 가장 적합한 함수를 경사하강법으로 찾아냄.

한계 보완 - A Survey on LLM-powered Agents for Recommender Systems

논문에서 제시한 LLM 식 접근법

Let a ∈ A denote an agent equipped with a set of functional modules F = F1, F2, ..., FK, where each module Fk represents a specific capability. The recommendation process for a user u can be formally expressed as: y^u = f(Fk(Xu)), k = 1 · · · K where Xu ∈ X represents the input space containing user specific information (e.g., interaction history, contextual features), and y^u ∈ R N denotes the predicted preference distribution over the item space.

X_u = 유저 개인의 interaction history

F_k = X_u 의 y^u 에 대한 함수

F = F_k 를 통과한 값들을 다 더해서 하나의 값으로 만들어주는 함수 (시그마나 적분 , 정규화 가능)

사실상 앞의 전통적인 방식과 접근 자체는 똑같다. 하지만, llm 의 경우는 user 의 interaction 별로 함수를 찾는것이고 , 기존의 방식은 , user 의 interaction 전체를 대상으로 한 함수를 찾는 것이다.

한계 보완 - A Survey on LLM-powered Agents for Recommender Systems

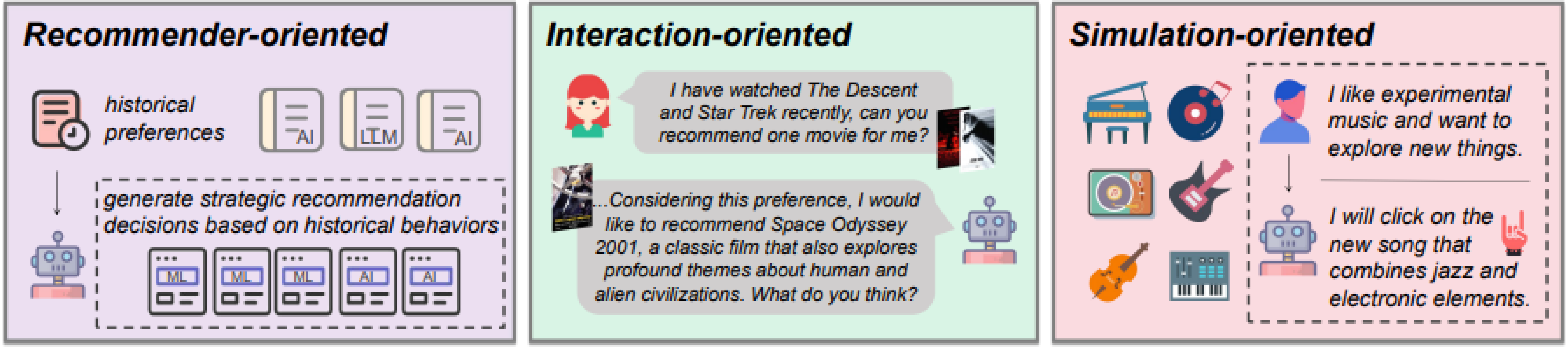


Figure 1: Illustration of Different Method Objectives. We classify existing methods into the following three categories: (1) Recommender-oriented method; (2) Interaction-oriented method; (3) Simulation-oriented method.

(1) Recommendation Oriented

(1) Recommender-oriented approaches focus on developing intelligent recommendation equipped with enhanced planning, reasoning, memory, and tool-using capabilities. In these approaches, LLMs leverage users' historical behaviors to generate direct recommendation decisions. For instance, as shown in Figure 1, when a user demonstrates recent engagement with technology news and AI-related content, the system might strategically recommend: "Here are 5 articles about latest large language model breakthroughs, 3 introductory articles about machine learning basics, and 2 popular science pieces about AI's impact on society." This paradigm demonstrates how agents can effectively combine their core capabilities to deliver direct item recommendations.

LLM 기반 reasoning + user modeling + context adaptation

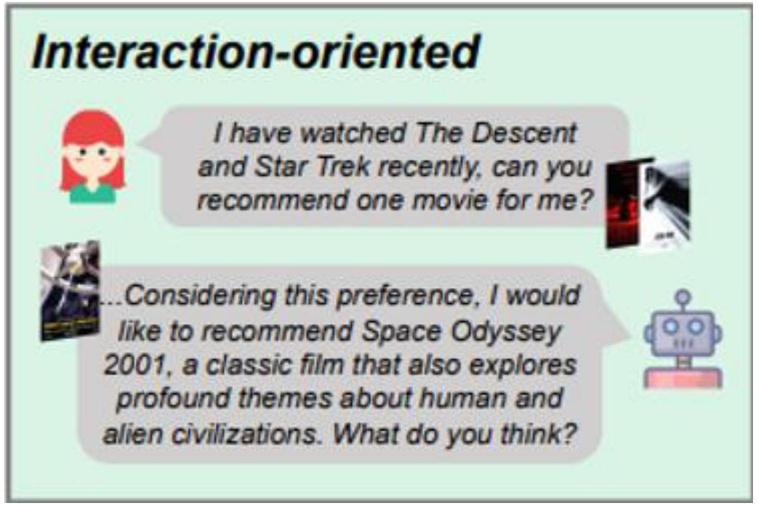
개인화, 맥락 기반 추천, 목표 달성 지원

(2) Interaction Oriented

(2) Interaction-oriented methods focus on enabling natural language interaction and enhancing recommendation interpretability through conversational engagement. These approaches utilize LLMs to conduct human-like dialogues or explanation while making recommendations. For example, as shown in Figure 1, an LLM might respond to a user query with: "I noticed that you like science fiction movies, especially after watching The Descent and Star Trek recently. Considering this preference, I would like to recommend Space Odyssey 2001, a classic film that also explores profound themes about human and alien civilizations. What do you think?" Such interactive recommendations showcase the agent's ability to not only track user preferences but also articulate recommendations in a conversational manner, explaining the reasoning behind suggestions.

사용자와의 대화를 통해서 추천을 이끌어냄.

- 실제 유저 반응 반영
- 현실 적응력 높음
- personalization 즉각 반영



(3) Simulation Oriented

(3) Simulation-oriented methods aim to authentically replicate user behaviors and preferences through sophisticated simulation techniques. These approaches leverage LLMs to generate realistic user responses to recommendations. For instance, when simulating user feedback, an LLM might generate: “As a user who is keen to explore new music, I will click on this new song that combines jazz and electronic elements because it matches my interest in experimental music while maintaining the rhythmic style that I like.” These methods focus on using agents to simulate user behaviors and item characteristics in RSs.

앞의 interaction oriented 는 실제 사용자 반응에 맞춰서 지속적으로 적응하는것이라면 , Simulation oriented 는 가상의 환경에서 최적화된 행동을 찾는다.

- 안전하게 대규모 실험 가능
- 위험 없는 exploration
- 반복 가능

Recommendation system 시장의 현재 동향

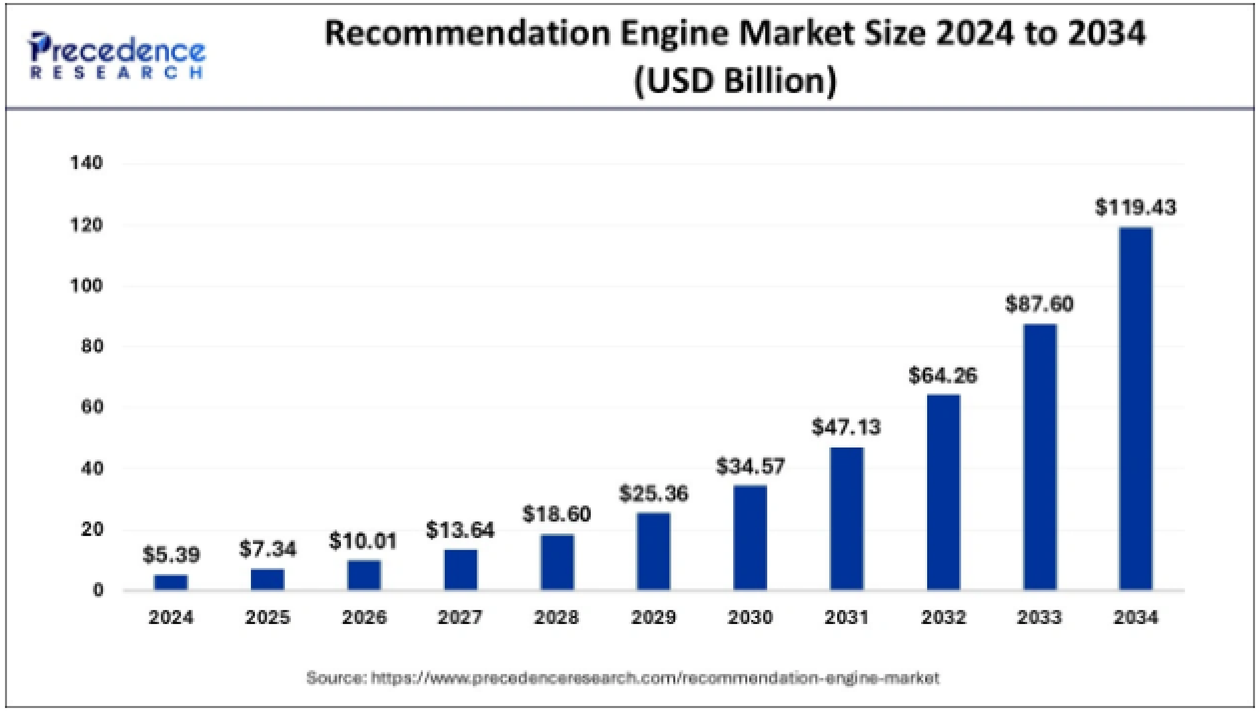
- https://www.grandviewresearch.com/press-release/global-recommendation-engine-market

- https://www.mordorintelligence.com/industry-reports/recommendation-engine-market

- https://www.precedenceresearch.com/recommendation-engine-market

Recommendation system 시장의 현재 동향

링크



추천시스템 자체의 시장도 아주 좋은 지수적 증가를 보이고 있다.

이는 추천시스템의 핵심인 개인화와 데이터 분석이 AI 의 도입을 통해 AI agent 로 합쳐지면서, 더 세분화된 추천을 제공할 가능성이 다분하기 때문이다.

Recommendation system 시장의 현재 동향

Artificial Intelligence (AI) Integration in the Recommendation Engine Market

Artificial intelligence is playing a crucial role in the transformation of the recommendation engine market. It is able to analyze vast amounts of data, making it easy to improve consumer experiences. AI is able to provide accurate real-time suggestions that help to improve sales and consumer engagement. Increased demand for recommendation engines is urging manufacturers to adopt the AI system. Some AI integrations, like multi-modal recommendation systems and cloud-based deployments, are helping by providing personalized suggestions through text, images, and user preferences and improving the scalability and flexibility of the systems.

Companies are eagerly adopting AI for the advantages of real-time monitoring and recommendations. The advancements in AI and ML technologies for more accurate and effective recommendations are leading to more adoption of artificial intelligence and machine learning technologies. The ability of AI and ML to analyze vast and complex data is enhancing the recommendation engines. It makes easy choices and is cost-effective, which attracts consumers. With the information provided by AI on customers' behavior, references, and interactions, businesses are able to develop and offer personalized recommendation systems with more effectiveness and scalability.

- In January 2024, the recommender system support for AI-driven recommendation engines, which provides spectacular advancements in AI technology, was launched by Arthur, a U.S.-based AI performance platform. This technology provides ways for online businesses to use recommender systems in the digital economy.

Recommendation system 시장의 현재 동향

Do you have any questions? Would you like to request a sample or make an inquiry before purchasing this report? Simply click the link below: https://www.polarismarketresearch.com/industry-analysis/recommendation-engine-market/request-for-sample

Big data analytics has become a powerful tool for improving the effectiveness of recommendation engines. Businesses can now track user activities, such as browsing habits, purchase history, and interaction with content with access to vast amounts of consumer data. This data is then used by recommendation systems to create highly personalized experiences, improving the chances of making accurate suggestions. As data collection and analysis techniques continue to improve, recommendation engines become smarter and more efficient at predicting customer preferences. This deeper understanding of user behavior boosts the relevance of recommendations, helping businesses optimize their marketing strategies and improve customer satisfaction.

링크

Recommendation system 시장의 전망

Ai agent 도입으로 보완 가능한 부분 :

유저별 데이터 분석 계산량을 높일 수 있다 (더 세부적인 요소까지 계산에 포함)
실시간 추천 가능 (사용자와의 대화에 따른 context – based 추천 가능)
멀티 모달 추천 (다양한 input (이미지 , 동영상 등) 을 기반으로 추천 가능)

다른 Agent 와의 동적인 연동을 통해 필요한 agent 를 호출하여 문제를 해결 가능함.

N8n 을 활용한 Recommendation agent

완전한 Recommendation agent 는 아니지만, 기능을 똑같이 구현한 사례가 있어서 가지고 와 봤습니다.

[n8n 링크]