Large Language Models for Recommendation: Progresses and Future Directions

Jizhi Zhang
cdzhangjizhi@mail.ustc.edu.cn
University of Science and Technology of China

Keqin Bao
baokq@mail.ustc.edu.cn
University of Science and Technology of China

Yang Zhang
zy2015@mail.ustc.edu.cn
University of Science and Technology of China

Wenjie Wang
wenjiewang96@gmail.com
National University of Singapore

Fuli Feng
fulifeng93@gmail.com
University of Science and Technology of China

Xiangnan He
xiangnanhe@gmail.com
University of Science and Technology of China

ABSTRACT

Large language models (LLMs) have significantly influenced recommender systems. Both academia and industry have shown growing interest in developing LLMs for recommendation purposes, an approach commonly referred to as LLM4Rec. This involves efforts such as utilizing LLMs for generative item retrieval and ranking, along with the potential for creating universal LLMs for varied recommendation tasks, signaling a possible paradigm shift in recommender systems. This tutorial is designed to review the progression of LLM4Rec and provide an in-depth analysis of the prevailing studies. We will discuss how LLMs advance recommender systems in model architecture, learning paradigms, and capabilities like conversation, generalization, planning, and content generation. Additionally, the tutorial will highlight open problems and challenges in this nascent field, addressing concerns related to trustworthiness, efficiency, online training, and recommendation data modeling. Concluding with a summary of the takeaways from previous research, the tutorial will suggest avenues for future investigations. Our aim is to help the audience grasp the developments in LLM4Rec, as well as to spark inspiration for further research. By doing so, we expect to contribute to the growth and success of LLM4Rec, possibly leading to a fundamental change in recommender paradigms.

CCS CONCEPTS

• **Information systems** → **Recommender systems**.

KEYWORDS

Large Language Models, Recommender Systems, Generative Recommendation, Generative Models

ACM Reference Format:
Jizhi Zhang, Keqin Bao, Yang Zhang, Wenjie Wang, Fuli Feng, and Xiangnan He. 2024. Large Language Models for Recommendation: Progresses and Future Directions. In *Companion Proceedings of the ACM Web Conference 2024 (WWW '24 Companion), May 13–17, 2024, Singapore, Singapore.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3589335.3641247

WWW '24 Companion, May 13–17, 2024, Singapore, Singapore

ACM ISBN 979-8-4007-0172-6/24/05…$15.00
https://doi.org/10.1145/3589335.3641247

1 FORMAT AND INTENDED AUDIENCE

• **Format.** This is a half-day (3 hours plus breaks) lecture-style tutorial, conducted on-site. All tutorial presenters plan to attend the conference in person.
• **Intended audience.** This tutorial is tailored to data scientists, machine learning engineers, and researchers interested in harnessing the potential of large language models (LLMs) for recommender systems. It presupposes that the audience possesses an introductory understanding of recommendation techniques. The tutorial will give an induction of the fundamental concepts and capabilities of LLMs, facilitating the audience's comprehension of the progress and future trajectories of LLM-enhanced recommender systems, and offering insights into their practical applications or research possibilities. Furthermore, this tutorial extends its relevance to researchers and practitioners in various information retrieval domains beyond recommendation, who aspire to leverage the power of LLMs for their specific tasks.

2 PRESENTERS

Jizhi Zhang[1] is a Ph.D. student at University of Science and Technology of China (USTC), supervised by Prof. Fuli Feng and Prof. Xiangnan He. His research interest lies in the recommender system and large language models. He has several publications in top conferences such as WWW, RecSys, SIGIR, and ACL.

Keqin Bao[2] is a Ph.D. student at University of Science and Technology of China (USTC), supervised by Prof. Fuli Feng and Prof. Xiangnan He. His research interest lies in the recommender system and large language models. He has several publications in top conferences such as RecSys.

Yang Zhang[3] is a Ph.D. student at the University of Science and Technology of China (USTC), supervised by Prof. Xiangnan He. His research interest lies in the recommender system. He has over ten publications that appeared in top conferences/journals. His work on recommendation has received the Best Paper Honorable Mention in SIGIR 2021. He has served as the PC member and reviewer for

[1] https://data-science.ustc.edu.cn/_upload/tpl/12/b5/4789/template4789/author/jizhi-zhang.html.
[2] http://data-science.ustc.edu.cn/_upload/tpl/12/b5/4789/template4789/author/keqin-bao.html.
[3] https://scholar.google.com/citations?user=M9NcazMAAAAJ.

the top conferences and journals including TKDE, TOIS, RecSys, WSDM, WWW, SIGIR, and KDD. He has presented the tutorial on recommendation in WWW 2022 and SIGIR 2023.

Wenjie Wang[4] is a research fellow at the School of Computing, National University of Singapore. He received Ph.D. in Computer Science from National University of Singapore in 2023. His research interests cover causal recommendation, data mining, and multimedia. His publications appear in several top conferences and journals such as SIGIR, KDD, WWW, ACM MM, and TIP. Moreover, he has served as the PC member and reviewer for the top conferences and journals including TPAMI, TOIS, SIGIR, WWW, and KDD. He has presented tutorials in WWW 2022 and SIGIR 2023.

Fuli Feng[5] is a professor at the University of Science and Technology of China. His research interests include information retrieval, data mining, causal inference, and multi-media processing. He has over 60 publications appeared in several top conferences such as SIGIR, WWW, and SIGKDD, and journals including TKDE and TOIS. He has received the Best Paper Honourable Mention of SIGIR 2021 and Best Poster Award of WWW 2018. Moreover, he has served as the reviewer for several top conferences and journals, including SIGIR, WWW, SIGKDD, NeurIPS, ICML, ICLR, ACL, TOIS, TKDE, TNNLS, TPAMI. He has rich teaching experience and has organized tutorials at SIGIR'23, WWW'21&22&23, and RecSys'21.

Xiangnan He[6] is a professor at the University of Science and Technology of China (USTC). His research interests span information retrieval, data mining, and applied machine learning. He has over 100 publications appeared in top conferences such as SIGIR, WWW, and KDD, and journals including TKDE, TOIS, and TNNLS. His work on recommender system has received the Best Paper Award Honourable Mention in SIGIR (2023, 2021, 2016) and WWW (2018). He has rich teaching experience and has organized tutorials at SIGIR'18&20&23, WSDM'19&20&22, WWW'18&21&22, CIKM'19, and RecSys'21.

3 TOPIC AND RELEVANCE

3.1 Motivation

Recommender systems have become an integral part of our digital lives, providing personalized recommendations regarding products, services, and content [1]. Looking back at the history of recommender systems, language models (LMs) are essential in shaping the landscape of recommender algorithms.

In terms of model architecture, sequential recommendation has drawn inspiration from the Transformer architecture, giving rise to innovative approaches like BERT4Rec [47] and SASRec [33]. Regarding learning paradigms, recommender models have also embraced the two-stage paradigm of pre-training and fine-tuning [36, 43], as well as prompt learning for multiple tasks [14, 22]. Notably, earlier models such as P5 [22] and M6-Rec [14] have explored the potential of a unified LM to seamlessly handle various recommendation tasks, such as click-through rate prediction, sequential recommendation, explanation generation, and conversational recommendation. However, it is worth noting that these earlier studies depend on medium-size LMs with limited generalization capabilities, often necessitating extensive recommendation data for training [22, 27].

Recently, the advent of powerful LLMs has significantly sparked technical advances in the field of recommender systems, opening up new horizons of leveraging LLMs for recommendation (shorted as LLM4Rec). These LLMs exhibit remarkable language understanding and generation capabilities, generalization prowess, and planning abilities [42, 74]. In light of these, in-context learning-based [15, 21] and instruction tuning-based recommendations [7, 69] with few-shot data, have garnered substantial attention within the research community. As such, it is really opportune to organize this tutorial to examine the progress of LLM4Rec.

In addition to the progress of LLM4Rec, this tutorial will demonstrate and analyze its critical challenges. The trustworthiness issues in recommendations generated by LLMs remain a primary concern, including problems like bias & fairness, privacy, and safety. Besides, efficiency is another essential aspect. LLMs are computationally demanding, thus deploying LLMs into real-time recommendation systems requires careful optimization and resource management. Additionally, the dynamic nature of user preferences necessitates timely model retraining to keep recommendations up to date. It is also challenging to achieve timely retraining in LLM4Rec. Lastly, recommendation data might encompass collaborative filtering signals, long interaction sequences from users, and high-dimensional features, which are also hard for LLMs to capture or utilize.

Last but not least, this tutorial will summarize the implications of previous work and present future research directions. In the future, it is essential to construct the evaluation benchmarks for LLM4Rec. Moreover, personalized AI-generated content might significantly facilitate the boom of generative recommendations [51]. As we delve into this tutorial, we aim to empower researchers and practitioners with knowledge and inspiration about LLM4Rec, inspiring further exploration and innovation in this emerging field.

Necessity and timely of this tutorial. LLM4Rec is a new topic, but developing vigorously. In the past years, there emerge extensive relevant papers [5, 7, 18, 59, 68]. Besides, some relevant workshops are hosted at CIKM'23[7]. Furthermore, researchers also actively organize special issues on TOIS[8] and TORS[9]. It is undoubted that more research endeavors will surface in this field, leading to more reliable and powerful recommender systems. Given the potential and rapid development of LLM4Rec, it is a suitable time to conduct this tutorial, benefiting researchers and industrial developers to learn the progress and future directions of LLM4Rec.

3.2 Objective

The aim of this tutorial is to offer a comprehensive grasp of LLM development for recommendation, encompassing the motivation, significance, current advancements, hurdles, and future directions. Additionally, this tutorial strives to empower participants with the expertise and capabilities needed to harness LLMs for their own projects and make contributions to the progress of related domains, such as advertising.

[4]https://scholar.google.com/citations?user=Ma5DtmoAAAAJ&hl=en.
[5]https://scholar.google.com.sg/citations?user=QePM4u8AAAAJ&hl=en.
[6]https://scholar.google.com.sg/citations?user=X45Go24AAAAJ.
[7]https://uobevents.eventsair.com/cikm2023/workshops.
[8]https://dl.acm.org/journal/tois/calls-for-papers.
[9]https://dl.acm.org/journal/tors/calls-for-papers.

3.3 Relevance

This tutorial holds strong relevance to the core domains of the Web Conference, especially related to user modeling and recommendation. Its subject matter is emerging as a crucial and thriving direction within the realm of recommendation, potentially serving as a source of inspiration for other related Web applications such as search and Web mining. Before proposing this tutorial for WWW'24, there is a related tutorial [30] at RecSys'23. This RecSys tutorial primarily spotlights technical aspects and mostly covers the studies on medium-size LMs. In contrast, our tutorial focuses more on LLMs for recommendation, and discuss the underlying reasons and advantages of developing LLMs for recommendations. We will also delve into broader, distinct challenges within the realm of LLM4Rec. Besides, there are two workshops [10] covering similar topics scheduled for CIKM 2023. Both the RecSys tutorial and CIKM workshops have garnered huge attention. Given WWW's close affiliation with RecSys and CIKM, we anticipate that our tutorial will also attract significant interest from the WWW community.

3.4 Outline

We present an outline of the topics to be covered with timing:

- Introduction. (15 Min, Xiangnan He)
  - Organization of the tutorial.
  - Background of recommender systems.
  - The development of LMs.
  - LMs for recommendation.
    - Utilizing LMs' model structure for recommendation [36, 47].
    - LM as item encoder [27, 29, 66].
    - Recommendation as natural language processing [14, 22].
- Progresses of LLM4Rec (60 Min, Keqin Bao, Jizhi Zhang)
  - Development of LLMs [2, 42, 74].
  - Benefits of LLMs for recommendations [37].
  - LLMs for recommendation.
    - In-context learning-based recommendation.
      - Directly utilizing in-context learning for recommendation [15, 21, 32, 41].
      - Combining in-context learning with conventional recommender models [28, 50, 57, 60].
    - Tuning-based LLM4Rec [5, 7, 39, 58, 69].
    - Chatting-enhanced LLM4Rec [19, 20].
    - Agent-based LLM4Rec [49, 55, 61, 67].
- Q&A. (5 Min)
- Break. (10 Min)
- Open problems and challenges of LLM4Rec. (60 Min, Yang Zhang, Wenjie Wang)
  - Efficiency of LLM4Rec.
    - Inference/Training costs [16, 17, 34, 40].
    - Deployment costs [64].
  - LLM4Rec retraining & online training.
    - Incremental learning for LLM4Rec [46].
    - Knowledge injection for LLM4Rec [10].
    - Data selection for LLM4Rec [38, 45].
  - Trustworthy LLM4Rec.
    - Fairness & Bias in LLM4Rec [31, 56, 62, 68].
    - Privacy in LLM4Rec [11, 73].
    - OOD & Robustness in LLM4Rec [8, 48, 68].
    - Safety in LLM4Rec [3, 4].
    - Explainable LLM4Rec [9, 70].
  - Recommendation data modeling in LLM4Rec.
    - Modeling lifelong user interaction sequences [38].
    - Injecting collaborative filtering signals [5, 65, 72].
    - High-dimensional features & interaction sparsity [25]
  - Evaluation & Benchmark of LLM4Rec [13, 26, 54].
- Conclusion and future directions. (25 Min, Fuli Feng)
  - Conclusion.
  - Generative Recommendation with LLMs [51].
- Q&A. (5 Min)

3.5 Qualification of presenters

We have been working on recommender systems for a long time with a series of publications [23, 24, 52, 71] that emerged in top-tier conferences and journals. Recently, we have also released several well-known papers about LLM4Rec [5, 7, 68], some of which are published at RecSys'23 [7, 68]. Besides, we organized a relevant workshop titled "Recommendation with Generative Models" at CIKM'23 [11] and a special issue on TOIS[12]. We are familiar with this field and will provide a systemic review and prospects of LLM4Rec. Moreover, our team has rich tutorial experience and has conducted more than 10 tutorials at various conferences including SIGIR, WWW, WSDM, CIKM, and RecSys [12, 35, 44, 53, 63]. We thus believe this tutorial would be attractive and insightful.

4 TUTORIAL DETAILS

- **Duration**. The tutorial is planned as a 3-hour tutorial.
- **Interaction style**. This is a lecture-style tutorial.
- **Tutorial materials**. The slides will be released on the tutorial website. Organizers can obtain copyright permission.
- **Previous editions**. Before this tutorial for WWW'24, we offer this tutorial at SIGIR-AP'23 [6] on Nov 26 2023. We collect audience feedback and further improve our tutorial for the WWW community. Besides, this field is developing rapidly, with novel studies emerging monthly. At WWW'24, we update the progress, open problems, and challenges of LLM4Rec, drawing insights from relevant work in 2023 and 2024.
- **Video teaser**. We have released the teaser through Dropbox [13].
- **Organization details**. The tutorial will be delivered in an onsite format, with all presenters physically presenting the tutorial. Additionally, we can prepare pre-recorded lectures if deemed necessary. Moreover, subject to approval, we are open to livestreaming the tutorial via popular video-streaming platforms.

REFERENCES

[1] Qingyao Ai et al. 2023. Information Retrieval Meets Large Language Models: A Strategic Report from Chinese IR Community. *AI Open* 4 (2023), 80–90.
[2] Rohan Anil et al. 2023. Palm 2 technical report. *arXiv preprint arXiv:2305.10403* (2023).
[3] Yuntao Bai et al. 2022. Constitutional ai: Harmlessness from ai feedback. *arXiv preprint arXiv:2212.08073* (2022).
[4] Yuntao Bai et al. 2022. Training a helpful and harmless assistant with reinforcement learning from human feedback. *arXiv preprint arXiv:2204.05862* (2022).

[10] https://uobevents.eventsair.com/cikm2023/workshops.

[11] https://rgm-cikm23.github.io/.
[12] https://dl.acm.org/journal/tois/calls-for-papers.
[13] https://www.dropbox.com/scl/fi/tvrhi7znmfynrtz6dz6ew/WWW24_tutorial.mp4?rlkey=8eb40ff5up0p02lnoyeclr38c&dl=0

[5] Keqin Bao et al. 2023. A Bi-Step Grounding Paradigm for Large Language Models in Recommendation Systems. *CoRR* abs/2308.08434 (2023). arXiv:2308.08434

[6] Keqin Bao et al. 2023. Large Language Models for Recommendation: Progresses and Future Directions. *SIGIR-AP* (2023).

[7] Keqin Bao et al. 2023. TALLRec: An Effective and Efficient Tuning Framework to Align Large Language Model with Recommendation. In *RecSys*. ACM, 1007–1014.

[8] Lukas Berglund et al. 2023. The Reversal Curse: LLMs trained on Ä is B̈fail to learn B̈ is A.: *arXiv preprint arXiv:2309.12288* (2023).

[9] Steven Bills et al. 2023. Language models can explain neurons in language models. *URL https://openaipublic. blob. core. windows. net/neuron-explainer/paper/index. html.(Date accessed: 14.05. 2023)* (2023).

[10] Boxi Cao et al. 2023. The Life Cycle of Knowledge in Big Language Models: A Survey. *arXiv preprint arXiv:2303.07616* (2023).

[11] Aldo Gael Carranza et al. 2023. Privacy-Preserving Recommender Systems with Synthetic Query Generation using Differentially Private Large Language Models. *arXiv preprint arXiv:2305.05973* (2023).

[12] Jiawei Chen et al. 2021. Bias Issues and Solutions in Recommender System. In *RecSys*. 825–827.

[13] Xu Chen et al. 2023. REASONER: An Explainable Recommendation Dataset with Multi-aspect Real User Labeled Ground Truths Towards more Measurable Explainable Recommendation. *arXiv preprint arXiv:2303.00168* (2023).

[14] Zeyu Cui et al. 2022. M6-rec: Generative pretrained language models are open-ended recommender systems. *arXiv preprint arXiv:2205.08084* (2022).

[15] Sunhao Dai et al. 2023. Uncovering ChatGPT's Capabilities in Recommender Systems. In *RecSys*. ACM, 1126–1132.

[16] Tri Dao et al. 2022. Flashattention: Fast and memory-efficient exact attention with io-awareness. *NeurIPS* 35 (2022), 16344–16359.

[17] Tim Dettmers et al. 2023. Qlora: Efficient finetuning of quantized llms. *arXiv preprint arXiv:2305.14314* (2023).

[18] Wenqi Fan et al. 2023. Recommender systems in the era of large language models (llms). *arXiv preprint arXiv:2307.02046* (2023).

[19] Yue Feng et al. 2023. A Large Language Model Enhanced Conversational Recommender System. *arXiv preprint arXiv:2308.06212* (2023).

[20] Luke Friedman et al. 2023. Leveraging Large Language Models in Conversational Recommender Systems. *arXiv preprint arXiv:2305.07961* (2023).

[21] Yunfan Gao et al. 2023. Chat-REC: Towards Interactive and Explainable LLMs-Augmented Recommender System. *CoRR* abs/2303.14524 (2023).

[22] Shijie Geng et al. 2022. Recommendation as language processing (rlp): A unified pretrain, personalized prompt & predict paradigm (p5). In *RecSys*. 299–315.

[23] Xiangnan He et al. 2017. Neural Collaborative Filtering. In *WWW*. ACM, 173–182.

[24] Xiangnan He et al. 2020. Lightgcn: Simplifying and powering graph convolution network for recommendation. In *SIGIR*. 639–648.

[25] Xiangnan He and Tat-Seng Chua. 2017. Neural Factorization Machines for Sparse Predictive Analytics. In *SIGIR*. ACM, 355–364.

[26] Zhankui He et al. 2023. Large language models as zero-shot conversational recommenders. *arXiv preprint arXiv:2308.10053* (2023).

[27] Yupeng Hou et al. 2022. Towards universal sequence representation learning for recommender systems. In *SIGKDD*. 585–593.

[28] Yupeng Hou et al. 2023. Large language models are zero-shot rankers for recommender systems. *arXiv preprint arXiv:2305.08845* (2023).

[29] Yupeng Hou et al. 2023. Learning vector-quantized item representation for transferable sequential recommenders. In *WWW*.

[30] Wenyue Hua et al. 2023. Tutorial on Large Language Models for Recommendation. In *RecSys*. 1281–1283.

[31] Meng Jiang et al. 2024. Item-side Fairness of Large Language Model-based Recommendation System. In *WWW*.

[32] Wang-Cheng Kang et al. 2023. Do LLMs Understand User Preferences? Evaluating LLMs On User Rating Prediction. *CoRR* abs/2305.06474 (2023).

[33] Wang-Cheng Kang and Julian McAuley. 2018. Self-attentive sequential recommendation. In *ICDM*. IEEE, 197–206.

[34] Woosuk Kwon et al. 2023. Efficient Memory Management for Large Language Model Serving with PagedAttention. *arXiv preprint arXiv:2309.06180* (2023).

[35] Wenqiang Lei et al. 2020. Conversational recommendation: Formulation, methods, and evaluation. In *SIGIR*. 2425–2428.

[36] Jiacheng Li et al. 2023. Text Is All You Need: Learning Language Representations for Sequential Recommendation. In *SIGKDD*. ACM, 1258–1267.

[37] Jianghao Lin et al. 2023. How Can Recommender Systems Benefit from Large Language Models: A Survey. *arXiv preprint arXiv:2306.05817* (2023).

[38] Jianghao Lin et al. 2023. ReLLa: Retrieval-enhanced Large Language Models for Lifelong Sequential Behavior Comprehension in Recommendation. *arXiv preprint arXiv:2308.11131* (2023).

[39] Xinyu Lin et al. 2023. A Multi-facet Paradigm to Bridge Large Language Model and Recommendation. *arXiv preprint arXiv:2310.06491* (2023).

[40] Xinyu Lin, Wenjie Wang, Yongqi Li, Shuo Yang, Fuli Feng, Yinwei Wei, and Tat-Seng Chua. 2024. Data-efficient Fine-tuning for LLM-based Recommendation. *arXiv preprint arXiv:2401.17197* (2024).

[41] Junling Liu et al. 2023. Is ChatGPT a Good Recommender? A Preliminary Study. *CoRR* abs/2304.10149 (2023).

[42] OpenAI. 2023. GPT-4 technical report. *arXiv preprint arXiv:2303.08774* (2023).

[43] Zhaopeng Qiu et al. 2021. U-BERT: Pre-training User Representations for Improved Recommendation. In *AAAI*. AAAI Press, 4320–4327.

[44] Zhaochun Ren et al. 2018. Information Discovery in E-commerce: Half-day SIGIR 2018 Tutorial. In *SIGIR*. 1379–1382.

[45] Zhiqiang Shen et al. 2023. SlimPajama-DC: Understanding Data Combinations for LLM Training. *arXiv preprint arXiv:2309.10818* (2023).

[46] Tianhao Shi, Yang Zhang, Zhijian Xu, Chong Chen, Fuli Feng, Xiangnan He, and Qi Tian. 2023. Preliminary Study on Incremental Learning for Large Language Model-based Recommender Systems. *arXiv preprint arXiv:2312.15599* (2023).

[47] Fei Sun et al. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In *CIKM*. 1441–1450.

[48] Jindong Wang et al. 2023. On the robustness of chatgpt: An adversarial and out-of-distribution perspective. *arXiv preprint arXiv:2302.12095* (2023).

[49] Lei Wang et al. 2023. RecAgent: A Novel Simulation Paradigm for Recommender Systems. *arXiv preprint arXiv:2306.02552* (2023).

[50] Lei Wang and Ee-Peng Lim. 2023. Zero-Shot Next-Item Recommendation using Large Pretrained Language Models. *CoRR* abs/2304.03153 (2023).

[51] Wenjie Wang et al. 2023. Generative recommendation: Towards next-generation recommender paradigm. *arXiv preprint arXiv:2304.03516* (2023).

[52] Xiang Wang et al. 2019. Neural Graph Collaborative Filtering. In *SIGIR*. ACM, 165–174.

[53] Xiang Wang et al. 2020. Learning and reasoning on graph for recommendation. In *WSDM*. 890–893.

[54] Xiaolei Wang et al. 2023. Rethinking the Evaluation for Conversational Recommendation in the Era of Large Language Models. *arXiv preprint arXiv:2305.13112* (2023).

[55] Yancheng Wang et al. 2023. Recmind: Large language model powered agent for recommendation. *arXiv preprint arXiv:2308.14296* (2023).

[56] Yifan Wang et al. 2023. A survey on the fairness of recommender systems. *ACM Transactions on Information Systems* 41, 3 (2023), 1–43.

[57] Wei Wei et al. 2023. Llmrec: Large language models with graph augmentation for recommendation. *arXiv preprint arXiv:2311.00423* (2023).

[58] Likang Wu et al. 2023. Exploring Large Language Model for Graph Data Understanding in Online Job Recommendations. *CoRR* abs/2307.05722 (2023).

[59] Likang Wu et al. 2023. A Survey on Large Language Models for Recommendation. *arXiv preprint arXiv:2305.19860* (2023).

[60] Yunjia Xi et al. 2023. Towards Open-World Recommendation with Knowledge Augmentation from Large Language Models. *CoRR* abs/2306.10933 (2023).

[61] Zhiheng Xi et al. 2023. The Rise and Potential of Large Language Model Based Agents: A Survey. *arXiv preprint arXiv:2309.07864* (2023).

[62] Chen Xu et al. 2023. Do llms implicitly exhibit user discrimination in recommendation? an empirical study. *arXiv preprint arXiv:2311.07054* (2023).

[63] Jun Xu et al. 2018. Deep learning for matching in search and recommendation. In *SIGIR*. 1365–1368.

[64] Minrui Xu et al. 2023. Unleashing the power of edge-cloud generative ai in mobile networks: A survey of aigc services. *arXiv preprint arXiv:2303.16129* (2023).

[65] Zhengyi Yang et al. 2023. Large Language Model Can Interpret Latent Space of Sequential Recommender. *arXiv preprint arXiv:2310.20487* (2023).

[66] Zheng Yuan et al. 2023. Where to Go Next for Recommender Systems? ID- vs. Modality-based Recommender Models Revisited. In *SIGIR*. ACM, 2639–2649.

[67] An Zhang et al. 2023. On Generative Agents in Recommendation. *arXiv preprint arXiv:2310.10108* (2023).

[68] Jizhi Zhang et al. 2023. Is ChatGPT Fair for Recommendation? Evaluating Fairness in Large Language Model Recommendation. In *RecSys*. ACM, 993–999.

[69] Junjie Zhang et al. 2023. Recommendation as instruction following: A large language model empowered recommendation approach. *arXiv preprint arXiv:2305.07001* (2023).

[70] Yongfeng Zhang et al. 2020. Explainable recommendation: A survey and new perspectives. *Foundations and Trends® in Information Retrieval* 14, 1 (2020), 1–101.

[71] Yang Zhang et al. 2021. Causal Intervention for Leveraging Popularity Bias in Recommendation. In *SIGIR*. 11–20.

[72] Yang Zhang et al. 2023. CoLLM: Integrating Collaborative Embeddings into Large Language Models for Recommendation. *arXiv preprint arXiv:2310.19488* (2023).

[73] Jujia Zhao et al. 2024. LLM-based Federated Recommendation. https://api.semanticscholar.org/CorpusID:267682268

[74] Wayne Xin Zhao et al. 2023. A survey of large language models. *arXiv preprint arXiv:2303.18223* (2023).