Self-Supervised Learning for Recommendation: Foundations, Methods and Prospects

Junliang Yu
The University of Queensland
Brisbane, Australia
jl.yu@uq.edu.au

Tong Chen
The University of Queensland
Brisbane, Australia
tong.chen@uq.edu.au

Hongzhi Yin*
The University of Queensland
Brisbane, Australia
h.yin1@uq.edu.au

ABSTRACT

Recommender systems have become a necessity in this Internet era to offer personalization. However, in contrast to the increasing ease of model building and deployment, the lack of user behavioral data still remains a major pain point for modern recommender systems that constantly compromises recommendation performance. Recently, self-supervised learning (SSL), which can enable training on massive unlabeled data with automatic data annotation, has achieved tremendous success in many fields and been applied to an ever-expanding range of applications including recommendation. Many recent studies have demonstrated that all kinds of recommendation models can be significantly improved through learning with well-designed self-supervised tasks and data augmentations. In this tutorial, we will provide a panorama of the research efforts on self-supervised recommendation. Specifically, the content includes: (1) foundations and overview of self-supervised recommendation; (2) a comprehensive taxonomy of existing self-supervised recommendation methods; (3) how to apply SSL to various recommendation scenarios; (4) limitations in current research and future research directions. Additionally, we release an open-source toolkit to facilitate empirical comparisons and methodological development of self-supervised recommendation methods (released at https://github.com/Coder-Yu/SELFRec).

CCS CONCEPTS

• **Information systems → Recommender systems**.

KEYWORDS

Self-Supervised Learning, Recommender Systems, Data Augmentation, Contrastive Learning

ACM Reference Format:
Junliang Yu, Tong Chen, and Hongzhi Yin. 2023. Self-Supervised Learning for Recommendation: Foundations, Methods and Prospects. In *Proceedings of Make sure to enter the correct conference title from your rights confirmation emai (WSDM '23).* ACM, New York, NY, USA, 4 pages. https://doi.org/XXXXXXX.XXXXXXX

*Contact person

WSDM '23, February 27–March 03, 2023, Singapore

ACM ISBN 978-1-4503-XXXX-X/18/06…$15.00
https://doi.org/XXXXXXX.XXXXXXX

1 MOTIVATION

Recommender systems [2, 3, 28, 29] have become a necessity in this Internet era to prevent information overload and offer personalized contents to users. However, despite the great ability to model complex user preferences, recommendation models often fail to take full advantage of their capacity due to highly sparse user behavioral data [13, 27]. As a natural antidote to the data scarcity issue, self-supervised learning (SSL) has recently received tremendous attention [1, 4, 6, 7, 9–11, 14, 25]. By designing self-supervised tasks and creating various data augmentations, SSL can reduce the dependency on manual labels and enable training on massive unlabeled data. Inspired by the success of SSL in other fields [1, 4, 6, 9, 10, 20], there is also an increasing trend to develop self-supervised recommender systems.

The early research efforts on self-supervised recommendation can be traced back to Autoencoder and GAN-based recommendation models [5]. After the pre-trained language model BERT [4] made a hit in 2018, SSL as an independent concept, came into the spotlight. The recommendation community then started to embrace SSL. Since 2020, SSL has enjoyed a period of prosperity. In the meantime, a series of distinctive self-supervised recommendation models have been proposed [15–17, 19, 21–23, 26, 30]. These works almost involve all the main recommendation topics and greatly enrich the SSL family. Some important questions also arise with these research progress: (1) What exactly is self-supervised recommendation? (2) What are the effective ways to design self-supervised tasks and data augmentations? (3) How can we apply SSL to certain recommendation scenarios? (4) Which type of self-supervised approach is the most effective? (5) What are the limitations of current research and potential opportunities for future research? Although encouraging results are reported in previous studies on self-supervised recommendation, these questions have not yet been systematically investigated. There is an urgent need for the answers to them in order to further promote this line of research. By delivering this tutorial, we can give our deliberate responses to these questions and thus benefit both industry and academia.

2 BRIEF OUTLINE OF THE TOPICS TO BE COVERED

In this tutorial, we will provide a panorama of self-supervised recommendation. Specifically, the topics to be covered include:

- **Foundations and overview of self-supervised recommendation**. We will give an exclusive definition and formulation of self-supervised recommendation, display the development of this line of research, and discuss its connections to related topics like pre-training and contrastive learning.

- **Taxonomy of self-supervised recommendation**. We will introduce a comprehensive taxonomy of self-supervised recommendation, which is based on the distinct characteristics of different self-supervised tasks. Particularly, the taxonomy divides existing self-supervised methods into four categories: contrastive, generative, predictive, and hybrid. For each category, we discuss its overall idea, representative methods, and pros and cons.
- **Applications of SSL in different recommendation scenarios**. We will share our experience of applying SSL to multiple recommendation scenarios including social recommendation, session-based recommendation, on-device recommendation and general graph recommendation to participants. Specifically, we will dive into the principle of SSL and demystify why SSL can improve recommendation performance.
- **Limitations and future research directions of self-supervised recommendation**. Current research efforts mainly focus on using SSL to improve recommendation accuracy. We will analyze the limitations of current research and identify some promising research directions which are worth exploring.
- **Benchmarking self-supervised recommendation**. We will release a library SELFRec[1] to benchmark self-supervised recommendation. It contains many representative methods and provides user-friendly interfaces for fast development of self-supervised recommendation models. The empirical comparison of different methods can be easily conducted with it under a fair experimental setting.

3 INTENDED AUDIENCE

The tutorial targets a broad range of audiences from recommendation to other related areas. Graduate students, practitioners, and academic and industrial researchers all can benefit from this tutorial. As for the prerequisite, basic knowledge of information retrieval and recommendation is preferred. The tutorial will also introduce the foundation for better audience engagement. After the tutorial, we expect the audience can: 1) grasp the basic concepts and taxonomy of self-supervised recommendation; 2) get a bird's-eye view of this realm to avoid getting lost in a bewildering array of self-supervised recommendation approaches; 3) keep up with the latest progress of self-supervised recommendation; and 4) know to apply SSL to common recommendation scenarios. We also aim to provide participants with an insightful discussion of the imitations in current research and future research directions.

4 FORMAT AND DETAILED SCHEDULE

The tutorial is delivered as a **lecture-style** tutorial (3 hours in duration). The schedule and detailed organization of the topics are as follows.

I. Introduction (20 mins)

(1) Overview of recommendation
(2) Foundations and development of self-supervised recommendation

II. Definition and Taxonomy of self-supervised recommendation(20 mins)

(1) Definition and formulation
(2) Connections to related concepts and topics
(3) Taxonomy and common paradigms

III. Representative Methods (30 mins)

(1) Contrastive Methods
(2) Predictive Methods
(3) Generative Methods
(4) Hybrid Methods

IV. Apply SSL to Different Scenarios (60 mins)

(1) SSL on social recommendation
(2) SSL on session-based recommendation
(3) Multi-view self-supervised recommendation
(4) Efficient self-supervised recommendation

V. Limitations and Future Research Trends (20 mins)
VI. Open-source Toolkit for Self-Supervised Recommendation (15 mins)
VII. Conclusions and Discussions (15 mins)

5 RELATED RESOURCES

This tutorial can be considered as an extension of our previous tutorial: Junliang Yu, Hongzhi Yin, and Tong Chen, Self-Supervised Learning in Recommendation: Fundamentals and Advances, at WWW 2022. The previous one is an online lecture-style tutorial (1.5 hour in duration). Compared with it, this 3-hour tutorial will cover more topics and is enriched with lots of new content. In particular, we will introduce our recent advances in this line of research. The in-person conference also provides us with opportunities to guide the audience to gain hands-on experience through using our open-source library on site.

In addition, there is a parallel tutorial: Chao Huang, Xiang Wang, Xiangnan He, and Dawei Yin, Self-Supervised Learning for Recommender System, at SIGIR 2022. However, we have a more inclusive panorama and provide a survey [24] and an open-source library on self-supervised recommendation as the auxiliary materials for better audience engagement.

We also have some papers which are relevant to this tutorial and listed as follows:

- Self-supervised recommendation on graphs [21–23, 26].
- Self-supervised recommendation on sequences [12, 16, 17].
- Self-supervised pre-training for recommendation [8].
- Self-supervised recommendation on resource-constrained devices [18].
- A survey paper on self-supervised recommendation [24].

6 TUTORIAL MATERIALS

The tutorial materials including the slides will be made available online in advance for attendees at: https://sslrec-wsdm.github.io. Our survey [24] and the listed papers on self-supervised recommendation are also available for download, which can help participants gain a deep and comprehensive understanding of this field. The open-source library SELFRec provides attendees with opportunities for hands-on experience of using self-supervised learning to improve recommendation models.

[1] https://github.com/Coder-Yu/SELFRec

7 WAYS TO ENCOURAGE AUDIENCE PARTICIPATION

At the beginning of the tutorial, we will play a video teaser to catch the eye of participants and stimulate interest. During this lecture-style tutorial, we will encourage the audience to think and ask. At the end of the tutorial, we will introduce our open-source library and provide attendees with hands-on experience.

8 QUALIFICATIONS OF PRESENTERS

Our team is the pioneer of this emerging research field, and has been consistently working on recommender systems for years. Together with co-authors, our work on self-supervised recommendation has been published at top-tier venues such as KDD, WWW, AAAI, CIKM, WSDM, ICDM, SIGIR etc. We also have abundant practice experience and have developed an open-source framework QRec[2] towards open benchmarking for recommender systems, which has received 1,300+ stars on GitHub.

8.1 Brief Biography

Junliang Yu is a final-year Ph.D. student with the School of Information Technology and Electrical Engineering at the University of Queensland, jointly advised by A/Prof. Hongzhi Yin and Prof. Zi (Helen) Huang. He received his Bachelor and Master degrees from Chongqing University. His research interests include recommender systems, social media analytics, deep learning on graphs, and self-supervised learning. His recent research mainly focuses on efficient and explainable self-supervised learning for recommendation. He has 10+ publications on top-tier international venues such as KDD, WWW, ICDM, CIKM, AAAI, SIGIR, VLDBJ, and TKDE. He also served as the conference PC member of AAAI, CIKM, IJCAI, etc, and the journal reviewer for TOIS, TIST, TNNLS, TKDE, etc. He has rich lecture experience and tutored one relevant course of social media analytics, and also has made oral presentations on multiple top-tier conferences.

Dr. Tong Chen is a Lecturer with the Data Science Discipline at The University of Queensland and a recipient of the ARC Discovery Early Career Reseracher Award. He received his PhD degree in Computer Science from The University of Queensland in 2020. Dr. Chen's research interests include data mining, machine learning, business intelligence, recommender systems, and predictive analytics. He has 60+ publications on top-tier international venues such as KDD, SIGIR, ICDE, AAAI, IJCAI, ICDM, WWW, TKDE, IJCAI, TOIS, CIKM, as well as the prestigious health informatics journal JBHI. He has been actively providing professional services to over 20 world-leading international conferences/journals in the fields of data mining, information retrieval and AI. For example, his roles include program committee member of WSDM, CIKM, SIGIR, KDD, ICDM and reviewer for TKDE, TOIS, TKDD and TNNLS. Dr. Chen's recent research has been focused on trustworthy and lightweight graph mining and recommendation algorithms to embrace the era of edge computing and AIoT. Dr. Chen has ample track records in lecturing, witnessed by his course design and delivery experience in business analytics, full-course teaching experience in social media analytics and database systems, as well as invited talks on cutting-edge recommender systems at the WWW'22 Tutorial, ICDM'20 NeuRec Workshop, Beihang University, and Zhejiang University. He was one of the 17 nominees for the Most Effective Teacher in the Faculty of EAIT, The University of Queensland in 2022.

Dr. Hongzhi Yin works as ARC Future Fellow and associate professor with The University of Queensland, Australia. He was recognized as Field Leader of Data Mining & Analysis in The Australian's Research 2020 magazine, the recipient of the 2022 AI 2000 Most Influential Scholar Honorable Mention in Data Mining (10 Years Impact), and featured among the World's Top 2% Scientists List published by Stanford University (Single Year Impact) and AD Scientific Index 2022 (5 Years Impact). He received his doctoral degree from Peking University in July 2014, and his Ph.D. Thesis won the highly competitive Distinguished Doctor Degree Thesis Award of Peking University. His current main research interests include recommender systems, graph embedding and mining, chatbots, social media analytics and mining, edge machine learning, trustworthy machine learning, decentralized and federated learning, and smart healthcare. He has published 220+ papers with H-index 52, including 22 most highly cited publications in Top 1% (CNCI), 120 CCF A and 70+ CCF B, 120 CORE A* and 70+ CORE A, such as KDD, SIGIR, WWW, WSDM, SIGMOD, VLDB, ICDE, AAAI, IJCAI, ACM Multimedia, ECCV, IEEE TKDE and TNNL, VLDB Journal and ACM TOIS. He has won 6 Best Paper Awards such as Best Paper Award at ICDE 2019, Best Student Paper Award at DASFAA 2020, ACM Computing Reviews' 21 Annual Best of Computing Notable Books and Articles, and Best Paper Award Nomination at ICDM 2018. Dr. Yin has rich lecture experience and taught 5 relevant courses such as information retrieval and web search, data mining, social media analytics, and responsible data science. He was nominated as Most Effective Teacher of EAIT Faculty in The University of Queensland for 2020, 2021 and 2022. He has delivered 12 keynotes, invited talks and tutorials at the top international conferences such as tutorials at WWW 2017, KDD 2017 and Web Conference 2022.

[2]https://github.com/Coder-Yu/QRec

REFERENCES

[1] Ting Chen, Simon Kornblith, Mohammad Norouzi, and Geoffrey Hinton. 2020. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*. PMLR, 1597–1607.

[2] Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, et al. 2016. Wide & deep learning for recommender systems. In *Proceedings of the 1st workshop on deep learning for recommender systems*. 7–10.

[3] Paul Covington, Jay Adams, and Emre Sargin. 2016. Deep neural networks for youtube recommendations. In *Proceedings of the 10th ACM conference on recommender systems*. 191–198.

[4] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2018. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).

[5] Min Gao, Junwei Zhang, Junliang Yu, Jundong Li, Junhao Wen, and Qingyu Xiong. 2020. Recommender Systems Based on Generative Adversarial Networks: A Problem-Driven Perspective. *arXiv preprint arXiv:2003.02474* (2020).

[6] Jean-Bastien Grill, Florian Strub, Florent Altché, Corentin Tallec, Pierre H Richemond, Elena Buchatskaya, Carl Doersch, Bernardo Avila Pires, Zhaohan Daniel Guo, Mohammad Gheshlaghi Azar, et al. 2020. Bootstrap your own latent: A new approach to self-supervised learning. *arXiv preprint arXiv:2006.07733* (2020).

[7] Tengda Han, Weidi Xie, and Andrew Zisserman. 2020. Self-supervised co-training for video representation learning. *arXiv preprint arXiv:2010.09709* (2020).

[8] Bowen Hao, Jing Zhang, Hongzhi Yin, Cuiping Li, and Hong Chen. 2021. Pre-Training Graph Neural Networks for Cold-Start Users and Items Representation. In *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*. 265–273.

[9] Kaiming He, Haoqi Fan, Yuxin Wu, Saining Xie, and Ross Girshick. 2020. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 9729–9738.

[10] Zhenzhong Lan, Mingda Chen, Sebastian Goodman, Kevin Gimpel, Piyush Sharma, and Radu Soricut. 2019. Albert: A lite bert for self-supervised learning of language representations. *arXiv preprint arXiv:1909.11942* (2019).

[11] Jiezhong Qiu, Qibin Chen, Yuxiao Dong, Jing Zhang, Hongxia Yang, Ming Ding, Kuansan Wang, and Jie Tang. 2020. GCC: Graph Contrastive Coding for Graph Neural Network Pre-Training. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 1150–1160.

[12] Ruihong Qiu, Zi Huang, Hongzhi Yin, and Zijian Wang. 2021. Contrastive Learning for Representation Degeneration Problem in Sequential Recommendation. *ACM International Conference on Web Search and Data Mining* (2021).

[13] Badrul Munir Sarwar. 2001. *Sparsity, scalability, and distribution in recommender systems*. University of Minnesota.

[14] Petar Velickovic, William Fedus, William L Hamilton, Pietro Liò, Yoshua Bengio, and R Devon Hjelm. 2019. Deep Graph Infomax.. In *ICLR (Poster)*.

[15] Jiancan Wu, Xiang Wang, Fuli Feng, Xiangnan He, Liang Chen, Jianxun Lian, and Xing Xie. 2021. Self-supervised graph learning for recommendation. In *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 726–735.

[16] Xin Xia, Hongzhi Yin, Junliang Yu, Yingxia Shao, and Lizhen Cui. 2021. Self-Supervised Graph Co-Training for Session-based Recommendation. In *Proceedings of the 30th ACM international conference on information and knowledge management*.

[17] Xin Xia, Hongzhi Yin, Junliang Yu, Qinyong Wang, Lizhen Cui, and Xiangliang Zhang. 2021. Self-Supervised Hypergraph Convolutional Networks for Session-based Recommendation. In *Thirty-Fifth AAAI Conference on Artificial Intelligence*. 4503–4511.

[18] Xin Xia, Hongzhi Yin, Junliang Yu, Qinyong Wang, Guandong Xu, and Quoc Viet Hung Nguyen. 2022. On-Device Next-Item Recommendation with Self-Supervised Knowledge Distillation. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 546–555.

[19] Xu Xie, Fei Sun, Zhaoyang Liu, Shiwen Wu, Jinyang Gao, Bolin Ding, and Bin Cui. 2020. Contrastive Learning for Sequential Recommendation. *arXiv preprint arXiv:2010.14395* (2020).

[20] Zhilin Yang, Zihang Dai, Yiming Yang, Jaime Carbonell, Russ R Salakhutdinov, and Quoc V Le. 2019. Xlnet: Generalized autoregressive pretraining for language understanding. *Advances in neural information processing systems* 32 (2019).

[21] Junliang Yu, Hongzhi Yin, Min Gao, Xin Xia, Xiangliang Zhang, and Nguyen Quoc Viet Hung. 2021. Socially-Aware Self-Supervised Tri-Training for Recommendation. In *KDD '21: The 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, Singapore, August 14-18, 2021*. ACM, 2084–2092.

[22] Junliang Yu, Hongzhi Yin, Jundong Li, Qinyong Wang, Nguyen Quoc Viet Hung, and Xiangliang Zhang. 2021. Self-Supervised Multi-Channel Hypergraph Convolutional Network for Social Recommendation. In *Proceedings of the Web Conference 2021*. 413–424.

[23] Junliang Yu, Hongzhi Yin, Xin Xia, Tong Chen, Lizhen Cui, and Quoc Viet Hung Nguyen. 2022. Are graph augmentations necessary? simple graph contrastive learning for recommendation. In *Proceedings of the 45th International ACM SIGIR Conference on Research and Development in Information Retrieval*. 1294–1303.

[24] Junliang Yu, Hongzhi Yin, Xin Xia, Tong Chen, Jundong Li, and Zi Huang. 2022. Self-Supervised Learning for Recommender Systems: A Survey. *arXiv preprint arXiv:2203.15876* (2022).

[25] Xiaohua Zhai, Avital Oliver, Alexander Kolesnikov, and Lucas Beyer. 2019. S4l: Self-supervised semi-supervised learning. In *Proceedings of the IEEE international conference on computer vision*. 1476–1485.

[26] Junwei Zhang, Min Gao, Junliang Yu, Lei Guo, Jundong Li, and Hongzhi Yin. 2021. Double-Scale Self-Supervised Hypergraph Learning for Group Recommendation. In *Proceedings of the 30th ACM international conference on information and knowledge management*.

[27] Shuai Zhang, Lina Yao, Aixin Sun, and Yi Tay. 2019. Deep learning based recommender system: A survey and new perspectives. *ACM Computing Surveys (CSUR)* 52, 1 (2019), 1–38.

[28] Guorui Zhou, Na Mou, Ying Fan, Qi Pi, Weijie Bian, Chang Zhou, Xiaoqiang Zhu, and Kun Gai. 2019. Deep interest evolution network for click-through rate prediction. In *Proceedings of the AAAI conference on artificial intelligence*, Vol. 33. 5941–5948.

[29] Guorui Zhou, Xiaoqiang Zhu, Chenru Song, Ying Fan, Han Zhu, Xiao Ma, Yanghui Yan, Junqi Jin, Han Li, and Kun Gai. 2018. Deep interest network for click-through rate prediction. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 1059–1068.

[30] Kun Zhou, Hui Wang, Wayne Xin Zhao, Yutao Zhu, Sirui Wang, Fuzheng Zhang, Zhongyuan Wang, and Ji-Rong Wen. 2020. Sˆ 3-Rec: Self-Supervised Learning for Sequential Recommendation with Mutual Information Maximization. *arXiv preprint arXiv:2008.07873* (2020).