Tutorial: Self-Supervised Learning in Recommendation: Fundamentals and Advances

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ABSTRACT

The neural architecture-based recommenders have demonstrated overwhelming advantages over their traditional counterparts. However, the highly sparse user behavior data often bottlenecks deep neural recommendation models to take full advantage of their capacity for better performance. Recently, self-supervised learning (SSL), which can enable training on massive unlabeled data with automatic data annotation, has received tremendous attention across multiple fields including recommender systems. It has turned out that SSL can significantly improve the recommendation quality by designing pretext tasks to discover supervisory signals from the raw data, serving as a natural antidote to the data sparsity issue. In this tutorial, we will systematically introduce the methodologies of applying SSL to recommendation. The topics to be covered include: (1) foundation and overview of self-supervised recommendation; (2) a comprehensive taxonomy of existing SSL-driven recommendation methods which is constructed based on the characteristics of pretext tasks; (3) how to apply SSL to various recommendation scenarios where different types of data and multiple optimization objectives are involved; (4) limitations in current research and future research directions; (5) 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, Contrastive Learning

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1 TOPIC AND RELEVANCE

The neural architecture-based recommender systems [3, 4, 32, 33] have demonstrated unprecedented strong performance and achieved outstanding success in recent years [1, 6]. However, despite the great ability to model complex user preferences, the deep neural recommendation models often fail to take full advantage of their capacity due to the highly sparse user behavioral data [15, 31]. As a natural antidote to the data scarcity issue [23, 24], self-supervised learning (SSL) has recently received tremendous attention [2, 5, 7, 8, 10, 11, 14, 17, 29]. By designing pretext tasks to extract supervisory signals from raw data, SSL can reduce the dependency on manual labels and enable training on massive unlabeled data. Inspired by the success of SSL on CV [2, 7, 10] and NLP [5, 11, 22], there is also an increasing trend towards developing self-supervised recommender systems.

Currently, a number of early research efforts have transplanted the ideas of SSL from other areas to recommendation [12, 16, 18, 21, 34], and some very recent works [13, 19, 20, 25, 26, 30] also have started to explore recommendation-specific SSL. These works almost span all kinds of recommendation topics, setting off a wave of research enthusiasm on this field. In the year of 2021, there have been more than 50 published papers and preprints focusing on self-supervised recommendation. Some important questions also arise with these research progress: (1) What are the differences between self-supervised recommendation and the traditional multi-task recommendation? (2) What are the common ways to design pretext tasks for different recommendation scenarios? (3) What is the principle behind self-supervised recommendation? (4) What are the limitations of current research and potential opportunities for future research? Although encouraging results are reported in existing works of self-supervised recommendation, these questions are not systematically investigated or even being neglected. There is an urgent need to reveal the answers of these questions, in order to further promote this line of research.

By delivering this tutorial, we give our deliberate responses to these questions and thus benefit both industry and academia:

- We aim to provide the participants with a broad picture of the current development of self-supervised recommendation. A timely and comprehensive literature review will be presented to help readers quickly grasp the basic concepts and step into this research field.
- We will share our experience of applying SSL to recommendation to the participants. Particularly, we will dive into the principle of SSL and demystify the recommendation performance gains brought by SSL with both experimental and theoretical analysis. We expect to introduce the basic guidelines for designing pretext tasks in practice to the participants.

- We aim to provide academic participants with an insightful discussion of the imitations in current research and future research directions. By releasing our toolkit for self-supervised recommendation, we expect to facilitate empirical comparisons and future methodological development of self-supervised recommendation methods.

2 THE TUTORIAL TEAM

Dr. Hongzhi Yin and his group are the pioneers of this emerging research field, and have been consistently working on recommender systems for years. Together with co-authors, their work on self-supervised recommendation has been published by top-tier venues such as KDD, WWW, AAAI, CIKM, WSDM, ICDM, etc. They also have abundant practice experience and have developed an open-source framework QRec[1] towards open benchmarking for recommender systems, which has received 1,000+ stars on GitHub.

2.1 Brief Bio of Organizers

Hongzhi Yin works as ARC Future Fellow and associate professor with The University of Queensland, Australia. He is leading the Responsible Big Data Intelligence Lab and was recognized as Field Leader of Data Mining & Analysis in The Australian's Research 2020 magazine. His current main research interests include recommender system, 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 180+ papers in the top conferences and journals, including 100+ CORE A* and 60+ CORE A, such as KDD (x15), IEEE TKDE (x14), SIGIR (x10), WSDM (x6), WWW (x6) and ACM TOIS (x11). He has won 6 Best Paper Awards such as ICDE'19 Best Paper Award, DASFAA'20 Best Student Paper Award, and ACM Computing Reviews' 21st Annual Best of Computing Notable Books and Articles as well as one invited paper in the special issue of KAIS on the best papers of ICDM 2018. He is currently serving as Associate Editor for Springer Nature Computer Science, Editorial Board of Journal of Computer Science and Technology (JCST), Big Data Networks (specialty section of Frontiers in ICT, Frontiers in Digital Humanities, Frontiers in Big Data and Frontiers in Computer Science), Information, Guest Editors of ACM Transactions on Intelligent Systems and Technology, Information Systems, and World Wide Web. 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 and 2021. He has delivered 12 keynotes, invited talks and tutorials at the top international conferences such as tutorials at WWW 2017 and KDD 2017.

Junliang Yu is a third-year Ph.D. student in 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.

Tong Chen is a Lecturer with the Data Science Discipline at The University of Queensland. 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 40+ 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 IJCAI'21 (SPC), WSDM'21, CIKM'21 and IJCAI'20, reviewer for TKDE, TOIS, TKDD and TNNLS, as well as session chair for conferences CIKM'21, VLDB'20, and DASFAA'20. Dr. Chen has ample track records in lecturing, witnessed by his course design and delivery experience in business analytics, teaching experience in social media analytics, as well as invited talks on cutting-edge recommender systems at the ICDM'20 NeuRec Workshop, Beihang University, and Zhejiang University.

2.2 Relevant Publications by the Organizers

- SSL on graphs for recommendation [25–27, 30].
- SSL on sequences for recommendation [19, 20].
- Pre-training for recommendation models [9].
- A survey paper on self-supervised recommendation [28].

3 STYLE AND DURATION

The tutorial is delivered as a lecture-style tutorial (1.5 hours in duration). The schedule and detailed organization of the topics are as follows.

I. Introduction (15 mins)

(1) Overview of Recommendation
(2) Overview of SSL in Recommendation

II. Taxonomy of Self-Supervised Recommendation Methods (15 mins)

(1) Definition of Self-Supervised Recommendation
(2) Taxonomy and paradigms

III. SSL Methods for Recommendation (45 mins)

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

IV. Limitations and Future Research Trends (10 mins)

V. Opensource Toolkit for Self-Supervised Recommendation (5 mins)

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

4 TARGETED AUDIENCE

The tutorial targets at a broad range of audiences from recommendation and other related areas, including academic and industrial researchers, graduate students, and practitioners. After the tutorial, we expect the audience will have a grasp of basic SSL strategies for enhancing recommendation, and gain real-world practice experiences through working on the released opensource toolkit. As for the prerequisite, basic knowledge of information retrieval and recommendation is preferred, and the tutorial will also introduce the foundation for better audience engagement.

5 TUTORIAL MATERIALS

The tutorial materials including the slides and video recordings will be made available online in advance for attendees via: https://ssl-recsys.github.io. To avoid the potential occurrence of technical problems, a pre-recorded lecture will be uploaded to YouTube beforehand, and the link can be found on the above GitHub homepage.

6 VIDEO TEASER

The video teaser is available at https://bit.ly/3o0qkLg.

REFERENCES

[1] 2020. Amazon's recommendation algorithm drives 35% of its sales. https://evdelo.com/amazons-recommendation-algorithm-drives-35-of-its-sales/

[2] 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.

[3] 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.

[4] 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.

[5] 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).

[6] Carlos A Gomez-Uribe and Neil Hunt. 2015. The netflix recommender system: Algorithms, business value, and innovation. *ACM Transactions on Management Information Systems (TMIS)* 6, 4 (2015), 1–19.

[7] 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).

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

[9] 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.

[10] 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.

[11] 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).

[12] Dongha Lee, SeongKu Kang, Hyunjun Ju, Chanyoung Park, and Hwanjo Yu. 2021. Bootstrapping User and Item Representations for One-Class Collaborative Filtering. *arXiv preprint arXiv:2105.06323* (2021).

[13] Jianxin Ma, Chang Zhou, Hongxia Yang, Peng Cui, Xin Wang, and Wenwu Zhu. 2020. Disentangled Self-Supervision in Sequential Recommenders. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 483–491.

[14] 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.

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

[16] Fei Sun, Jun Liu, Jian Wu, Changhua Pei, Xiao Lin, Wenwu Ou, and Peng Jiang. 2019. BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In *Proceedings of the 28th ACM international conference on information and knowledge management*. 1441–1450.

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

[18] 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.

[19] 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*.

[20] Xin Xia, Hongzhi Yin, Junliang Yu, Qinyong Wang, Lizhen Cui, and Xiangliang Zhang. 2020. Self-Supervised Hypergraph Convolutional Networks for Session-based Recommendation. *arXiv preprint arXiv:2012.06852* (2020).

[21] 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).

[22] 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).

[23] Junliang Yu, Min Gao, Jundong Li, Hongzhi Yin, and Huan Liu. 2018. Adaptive Implicit Friends Identification over Heterogeneous Network for Social Recommendation. In *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*. ACM, 357–366.

[24] Junliang Yu, Min Gao, Hongzhi Yin, Jundong Li, Chongming Gao, and Qinyong Wang. 2019. Generating reliable friends via adversarial training to improve social recommendation. In *2019 IEEE International Conference on Data Mining (ICDM)*. IEEE, 768–777.

[25] 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.

[26] 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.

[27] Junliang Yu, Hongzhi Yin, Xin Xia, Tong Chen, Lizhen Cui, and Nguyen Quoc Viet Hung. 2022. Are Graph Augmentations Necessary? Simple Graph Contrastive Learning for Recommendation. (2022).

[28] 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).

[29] 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.

[30] 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*.

[31] 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.

[32] 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.

[33] 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.

[34] 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).