Self-Supervised Learning for Recommendation

Chao Huang
University of Hong Kong
chuang@cs.hku.hk

Lianghao Xia
University of Hong Kong
aka_xia@foxmail.com

Xiang Wang
University of Science and Technology of China
xiangwang1223@gmail.com

Xiangnan He
University of Science and Technology of China
hexn@ustc.edu.cn

Dawei Yin
Baidu
yindawei@acm.org

ABSTRACT

Recommender systems are playing an increasingly critical role to alleviate information overload and satisfy users' information seeking requirements in a wide spectrum of online platforms. However, the ubiquity of data sparsity and noise notably limits the representation capacity of existing recommender systems to learn high-quality user (item) embeddings. Inspired by recent advances of self-supervised learning (SSL) techniques, SSL-based representation learning models benefit a variety of recommendation domains. Such methods have achieved new levels of performance while reducing the dependence on observed supervision labels in diverse recommendation tasks. In this tutorial, we aim to provide a systemic review of state-of-the-art SSL-based recommender systems. To be specific, we summarize and categorize existing work of SSL-based recommender systems in terms of recommendation scenarios. For each type of recommendation task, the corresponding challenges and methods will be presented in a comprehensive way. Finally, some future directions and open questions will be raised to inspire more investigation on this important research line.

CCS CONCEPTS

• **Information systems** → **Recommender systems**; • **Computing methodologies** → **Learning latent representations**.

KEYWORDS

Self-Supervised Learning, Contrastive Learning, Recommender System, Collaborative Filtering, Graph Neural Networks

ACM Reference Format:
Chao Huang, Lianghao Xia, Xiang Wang, Xiangnan He, and Dawei Yin. 2022. Self-Supervised Learning for Recommendation. In *Proceedings of the 31st ACM International Conference on Information and Knowledge Management (CIKM'22), October 17–21, 2022, Atlanta, GA, USA.* , 4 pages. https://doi.org/10.1145/3511808.3557506

CIKM'22, October 17–21, 2022, Atlanta, GA, USA

ACM ISBN 978-1-4503-9236-5/22/10…$15.00
https://doi.org/10.1145/3511808.3557506

1 INTRODUCTION

Due to the rapid development of Internet technologies, the growing demand for attractive information has driven the advances of recommendation models in a variety of online user modeling platforms, such as e-commerce sites [1, 9], online streaming services [10], location-based services [6, 30] and news portals [23]. The goals of recommender systems are mainly two-folds: i) alleviate the information overload and facilitate the information-seeking process of users; ii) increase the business profitability and sales [17].

With the tremendous success of deep learning, neural network techniques have been widely used to improve the performance of various recommender systems, by addressing the shortcomings of conventional recommendation methods [14, 44, 46]. For example, multi-layer perceptrons (MLP) are used to enhance the shallow collaborative filtering models to enable the non-linear feature interactions, *e.g.*, NCF [12] and DeepFM [8]. To capture dynamic preferences of users, recurrent neural network-based methods (*e.g.*, GRU4Rec [13] and DIEN [47]) and convolutional neural network-based approaches (*e.g.*, Caser [22]) have shown their effectiveness in representation learning over item sequences. To incorporate user's social influence into user-item interaction modeling, attention mechanisms have been adopted as useful solutions for information aggregation in SAMN [2] and EATNN [3]. In modern recommender systems, diverse user interactions (*e.g.*, click, add-to-cart, review, purchase) present new challenges for conventional recommendation methods focusing on preference learning with single type of user-item interactions [16, 42]. To fill this gap, memory-augmented neural recommener system is proposed to model multi-typed of user interaction behaviors on items in MATN [31].

Recently, graph neural networks (GNNs) have emerged as the state-of-the-art paradigms for studying various recommendation problems. At the core of GNNs is the iterative embedding propagation which aggregates information from neighborhood nodes. With the stacked multiple propagation layers, the high-order neighbors' information can be preserved in the encoded node (user/item) embeddings [39]. Specifically, recent efforts leverage the strength of graph convolution to enhance the collaborative filtering by modeling the graph-based collaborative relationships, including NGCF [26] and LightGCN [11]. GNN-based social recommender systems propose to perform the information propagation over the user-user social graph and user-item interaction graph with the convolution-based GNN method (*e.g.*, KCGN [15]) and attention-based GNN approach (*e.g.*, GraphRec [5]). Furthermore, to differentiate behavior-aware interaction patterns between users and items, several GNN-based multi-behavior recommendation models have been proposed to capture the behavior heterogeneity in user preference learning, such as MBGCN [16] and KHGT [32]. In knowledge graph-enhanced recommender systems, graph neural networks are used to fuse neighborhood information over the knowledge graph for entity representation and knowledge-aware user preference modeling in recommendation, *e.g.*, KGAT [25] and KGCN [24].

While many efforts have been devoted to solving different recommendation tasks, the effectiveness of most existing methods may heavily rely on the sufficient high quality supervision labels. However, with the large number of items in recommender systems, the observed users' interactions are very sparse, leading to insufficient training labels for a large number of long-tail users and items. Additionally, noise is ubiquitous in the collected user behavior data from various online user modeling applications, such as the interaction noise and popularity bias. The ubiquity of noise presents challenges for learning quality embeddings of users (items) in recomender systems. Recently, self-supervised learning (SSL) has emerged as a promising solution to reduce the dependence on observed supervision labels in data representation learning. In general, self-supervised learning models aim to supplement the main supervised task with the auxiliary tasks, by exploring the additional supervision signals from data itself. With such design, SSL is able to provide auxiliary signals from unlabeled data for enhancing representation learning performance.

Considering the limitations of existing recommender systems, we believe it is essential to design self-supervised learning-based methods in tacking the data sparsity and noise challenges in a variety of recommendation tasks. With the consideration of the diverse learning context in different recommendation scenarios, it is difficult to directly apply the existing SSL methods proposed for image or language data to solve the recommendation problems. In this tutorial, we will introduce up-to-date self-supervised learning-based recommender systems proposed to address the key challenges in a wide spectrum of real-life recommendation scenarios.

2 TUTORIAL CONTENT

This tutorial will summarize the advances of self-supervised learning technologies in various recommendation scenarios. In particular, we will present how recent research work enhances various recommender systems with self-supervised learning methods and address the corresponding challenges. Different categories of recommender systems will be covered in this tutorial with specific goals:

- Introduce the preliminary knowledge of self-supervised learning technologies and different types of recommender systems.
- Describe the key challenges for each category of recommender system and the corresponding state-of-the-art related work. Furthermore, we will explain why it is worth the efforts of developing SSL-based models for each type of recommendation scenario.
- Present recent development of self-supervised learning-based recommender systems and how they enhance the recommendation performance with effective data augmentation.
- Discuss the experimental settings and results for self-supervised learning-based recommender systems in different categories of recommendation scenarios in real-world settings.
- Discuss future research directions and open questions on advancing recommender system research with self-supervised learning.

General Collaborative Filtering. Collaborative filtering (CF) is a widely adopted solution for personalized recommendation with the consideration of users may share similar interests if similar interaction behaviors can be observed for them. By exploring users' historical interactions, CF paradigm maps users and items into latent embedding space with the generated low-dimensional user and item representations. To model the high-order relationships among users and items, recent studies leverage graph neural networks to capture the complex interaction patterns with the graph-based message passing methods [4, 26]. In GNN-based CF approaches, by stacking multiple graph layers, high-order neighborhood information can be aggregated during the cross-layer embedding propagation. While graph neural networks can better capture the high-order relationships in CF and make impressive achievements, most of GNN-based collaborative filtering models are still restricted by the data sparsity and noise limitations [28].

To bring the advantage of self-supervised learning into general collaborative filtering paradigms, recent research work proposes to enhance CF via offering supplementary self-supervision signals from different perspectives. In particular, SGL [28] performs graph structure augmentation to generate contrastive views for self-supervising. To achieve the agreement between local and global dependencies, HCCF [33] and NCL [18] design local-global contrastive learning paradigms for data augmentation. SimGCL [33] proposes to construct contrastive views by adding uniform noise to embeddings. To alleviate data noise issue, SHT [34] designs a new self-supervised learning paradigm to supplement the main supervised task, in order to improve the robustness of recommender system against noise perturbation.

Social Recommendation. To exploit social influence among users to boost the quality of recommendation, social recommender systems are developed to fuse information from both user-user connections and user-item relationships. For example, GraphRec [5], DiffNet [29], and KCGN [15] are built over graph neural network with the recursive message passing over the user social graph and interaction graph structures. Inspired by the success of self-supervised learning for data augmentation, several recent studies aim to incorporate self-supervised signals into social recommenders, through the mutual information maximization between different representation views, such as MHCN [41], SMIN [19] and SEPT [40]. In those approaches, the constructed self-supervised learning tasks utilize the joint learning scheme to transfer knowledge between the social dimension and collaborative dimension for enhancing the representation learning of user preference.

Sequential Recommendation. Contrastive learning has also benefited sequential recommender systems to provide self-supervision signals in learning dynamic user preference over users' item sequences. For example, S^3-Rec [48] proposes pre-training methods to construct self-supervised signals from the sequence data and the corresponding attributed information. CL4SRec [36] introduces three data augmentation strategies, *i.e.*, masking, cropping, and reordering, for sequence-level contrastive learning. DuoRec [21] uses contrastive learning to address the embedding degeneration issue in sequential recommendation.

Multi-Behavior Recommendation. Multi-behavior recommender systems aim to leverage different types of user behaviors (*e.g.*, click, review, add-to-cart) to assist the prediction on the target type of user-item interactions (*e.g.*, purchase, like). To model the correlations among multiple types of user behavioural patterns, attention mechanism is used for aggregating behavior-specific user embeddings, such as MATN [31]. Following the graph message passing schema, GNN-based multi-behavior recommendation models are proposed to model diverse behavior-specific user preference based on the user-item interaction graph with the awareness of behavior heterogeneity, including, MBGCN [16], MB-GMN [35], and MGNN [45]. By differentiating behavior-aware preference representation, the user embeddings encoded by multi-behavior recommenders can reflect diverse user intentions.

To improve the robustness of multi-behavior recommendation, recent efforts have been made towards designing auxiliary self-supervised learning tasks to help the target prediction tasks. For example, CML [27] and HMG-CR [37] explore auxiliary supervision signals with contrastive learning to consider behavior multiplicity and dependency. Additionally, in S-MBRec [7], the self-supervised behavior importance modeling task is introduced to correlate the target and auxiliary behaviors with a graph CF paradigm.

Knowledge Graph-based Recommendation. Knowledge Graph (KG) has been introduced into recommender systems as useful side information to capture the mutual relations among items. Earlier studies of embedding-based approaches attempt to directly apply KG embedding schemes to improve user representation in KG-based recommender systems, like CKE [43]. Due to the graph structural property of KG, graph representation learning techniques achieve the state-of-the-art performance in KG-based recommender systems. For example, graph convolution network and graph attention mechanism have been respectively adopted in KGCN [24] and KGAT [25] to build knowledge-aware recommender systems.

Recent works [20, 38, 49] introduce the contrastive learning into the knowledge graph-based recommender systems. Specifically, KGCL [38] performs contrastive learning over knowledge graphs and designs knowledge-aware augmentation on user interaction data. MCCLK [49] generates three contrastive views for self-supervision by modeling three types of connections, *i.e.*, user-item interactions, item-entity relations, as well as user-item-entity connections. CKER [20] proposes to reach the agreement between the user's interaction-aware and knowledge-aware preference.

3 TARGET AUDIENCE

This tutorial is intended for information retrieval and data mining researchers, practitioners and students who show interest in recently proposed self-supervised learning techniques in web mining and recommender systems. To be specific, we summarize several groups of target audience in this tutorial:

- Researchers and practitioners who would like to explore self-supervised learning techniques for solving the problems in various domains. This group of researchers may also gain some insights and motivations from this tutorial.
- Researchers and practitioners who aim to tackle the challenges of the data scarcity and noise in various recommendation tasks.
- Researchers and practitioners who work on proposing and developing effective recommender systems for a broad spectrum of online user modeling scenarios in real-life applications.

4 ORGANIZERS

Chao Huang is an assistant professor at the University of Hong Kong with appointments in Department of Computer Science and Musketeers Foundation Institute of Data Science. He obtained the PhD degree from the University of Notre Dame in USA. His research interests are broadly in deep learning, data mining and information retrieval, with an emphasis on graph representation learning, self-supervised learning, recommendation, and user behavior modeling. His research work has published in many major international conferences, such as KDD, SIGIR, WWW, CIKM, WSDM, AAAI, and journals, such as TKDE, TOIS, and TIST.

Lianghao Xia is currently a postdoctoral fellow in the Department of Computer Science & Musketeers Foundation Institute of Data Science, at the University of Hong Kong. His research interests include data mining, graph neural networks, self-supervised learning and recommendation. His research work appears in several refereed international conferences and journals such as KDD, SIGIR, AAAI, IJCAI, CIKM, WSDM, ICDE as well as TKDE, TOIS, TNNLS. He won He-Jingtang Innovation Prize of SCUT in 2021.

Xiang Wang is a professor at the University of Science and Technology in China. He received his Ph.D from National University of Singapore. His research works focus on information retrieval, data mining and explainable AI with the applications of recommender systems and social media analysis. His publications appeared in many top conferences, including SIGIR, WWW, KDD, NeurIPS, ICLR, and journals, such as TKDE and TOIS. He also serves as PC member and reviewers for academic conferences and journals, including NeurIPS, ICLR, SIGIR, KDD, JMLR, TKDE, etc.

Xiangnan He is a professor at the University of Science and Technology of China. He received the Ph.D. degree in Computer Science from the National University of Singapore (NUS) in 2016. His research work includes information retrieval, data mining, and multimedia analysis. His research work has been published in many top-tier conferences and journals, such as SIGIR, WWW, KDD, MM, NeurIPS, ICLR, CVPR, TKDE, TOIS, and TMM. His research work has received the Best Paper Award Honourable Mention in SIGIR 2016, 2021 and WWW 2018. He has served as the associate editor for journals, such as TOIS, TBD, and PC member for top-tier conferences including SIGIR, WWW, KDD, MM, etc.

Dawei Yin is currently a Senior Director of Engineering at Baidu inc. He is the manager of the search science team at Baidu. He served as the senior director at JD.com and senior research manager at Yahoo labs. His research work includes information retrieval, data mining and machine learning, with an emphasis on the recommender system, web search, question answering, pre-trained language model, video and image analysis. His research work received the best paper award in WSDM 2016, KDD 2016 and best student paper award in WSDM 2018.

ACKNOWLEDGMENTS

This work is supported by the research grants from the Department of Computer Science & Musketeers Foundation Institute of Data Science at the University of Hong Kong.

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