Learning and Reasoning on Graph for Recommendation

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ABSTRACT

Recommendation methods construct predictive models to estimate the likelihood of a user-item interaction. Previous models largely follow a general supervised learning paradigm — treating each interaction as a separate data instance and building a supervised learning model upon the *information isolated island*. Such paradigm, however, overlook relations among data instances, hence easily resulting in suboptimal performance especially for sparse scenarios. Moreover, due to the black-box nature, most models hardly exhibit the reasons behind a prediction, making the recommendation process opaque to understand.

In this tutorial, we revisit the recommendation problem from the perspective of graph learning and reasoning. Common data sources for recommendation can be organized into graphs, such as bipartite user-item interaction graphs, social networks, item knowledge graphs (heterogeneous graphs), among others. Such a graph-based organization connects the isolated data instances and exhibits relationships among instances as high-order connectivities, thereby encoding meaningful patterns for collaborative filtering, content-based filtering, social influence modeling, and knowledge-aware reasoning. Inspired by this, prior studies have incorporated graph analysis (*e.g.,* random walk) and graph learning (*e.g.,* network embedding) into recommender models and achieved great success. Together with the recent success of graph neural networks (GNNs), graph-based models have exhibited the potential to be the technologies for next-generation recommender systems. This tutorial provides a review on graph-based learning methods for recommendation, with special focus on recent developments of GNNs. By introducing this emerging and promising topic in this tutorial, we expect the audience to get deep understanding and accurate insight on the spaces, stimulate more ideas and discussions, and promote developments of technologies.

CCS CONCEPTS

• **Information systems → Recommender systems**.

KEYWORDS

Recommendation, Graph Learning, Graph Neural Network

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1 INTRODUCTION

In the era of information explosion, personalized recommendation has been at the core of many real-world applications, ranging from E-commerce (*e.g.,* Amazon and Alibaba), social networking (*e.g.,* Facebook and WeChat), and content sharing (*e.g.,* Instagram and Pinterest) platforms. It helps users to accurately and timely obtain items of interest from massive contents. Not surprisingly, recommendation techniques are attracting increasing attentions from both academia and industry, as witnessed by the increase in publications and dedicated workshops.

The prime goal of recommendation is to estimate how likely a user would adopt the target item, or more formally, the likelihood of a user-item interaction. Existing methods [14, 15, 22, 23, 34, 35] largely follow a general supervised learning paradigm with two key components — (1) transforming each interaction and its associated side information into a separate data instance, and (2) feeding these instances into a supervised learning model to perform predictions. For example, matrix factorization (MF) [22] and neural collaborative filtering (NCF) [15] treat a pair of user and item ID embeddings as an instance, and then separate inner product and nonlinear neural networks to make the predictions; Going beyond using IDs merely, factorization machine (FM) [23] and neural factorization machine (NFM) [14] additionally encode side information like user profiles and item attributions into an instance representation. This paradigm has achieved great success and been widely deployed in industry, such as [7, 17, 18, 23, 24].

Nevertheless, the adoption of **information isolated island** in such paradigm — modeling each interaction as an independent instance — overlooks the relations among instances, which might result in suboptimal performance [32, 36, 43]. In particular, forgoing relations would make an instance's representation dependent merely on its own pre-existing features; this causes the resulting model to suffer from the suboptimal representation ability of instances, especially when the interactions of inactive users, unpopular items, or infrequent features are sparse [32, 36, 43]. Moreover, the models built on a separate data instance largely work as a black-box — only providing a predictive result but hardly exhibiting the reasons behind a recommendation, such as collaborative signals in collaborative filtering [15, 17, 22] and knowledge-aware reasoning in knowledge graph-based recommendation [43]. Such black-box nature makes the decision-making process opaque to understand and hampers their further applications. Therefore, it is of crucial significance to explore and exploit the relations among interactions.

Graph is a powerful representation which presents data instances as nodes and describes their relationships as edges, instead of only considering each instance in isolated. Such a graph-based organization brings benefits to exploiting potential properties in graph analysis (*e.g.,* random walk) and graph learning (*e.g.,* network embedding) techniques. To be specific, random walk explores proximity among nodes via paths and then propagates labels over these paths — making similar nodes assigned with similar labels — such as label smoothness adopted by early semi-supervised learning methods [2]. Inspired by this, researchers leverage random walk to propagate users' preference scores from historical item nodes and output a preference distribution over unobserved items, such as Absorption [1] and ItemRank [10] over item-item correlation graph, RecWalk [20] over user-item bipartite graph, and TriRank [13] over user-item-aspect tripartite graph. While having achieved great success, random walk-based recommender models rely largely on heuristics or statistics, and lack trainable parameters to optimize the recommendation objective. Towards this end, network embedding (also well-known as graph embedding or node embedding) is introduced to learn latent representation for each node, such as high-order proximity leveraged in path-based methods [8, 21, 27], translation principle utilized in knowledge graph embedding methods [3, 19], and representation smoothness used in network embedding methods [11, 26]. Recent efforts like HPE [5], HOP-Rec [42], and CES [6] incorporate network embedding into the representation learning of recommenders, using direct connections within graph to enrich representations of user and item nodes. These methods have achieved strong performance in many recommendation tasks, verifying the significance of graphs' relational information.

Recent years have witnessed a tremendous interest in graph neural networks (GNNs) [12, 16, 29, 38]. The core idea is the information-propagation mechanism — aggregating information from a node's neighbors to enrich its representation and improve the downstream supervised learning. Benefiting from a such propagation effect, GNN-based methods have shown promising results and improved the state of the art in many challenging tasks, ranging from social influence detection in data mining, scene graph modeling in computer vision, to reading comprehension in natural language processing. Inspired by the recent success of GNNs, we believe that graph learning technologies serve as an infrastructure for next-generation recommendation. It is thus timely to revisit the recommendation problem from the perspective of graph learning and introduce the recent works on GNN-based recommenders. Here we focus on several recommendation scenarios as follows:

- **Collaborative Filtering:** User-item interaction data are organized as a bipartite graph between user and item nodes. Recent efforts like GC-MC [28], NGCF [36], and SpectralCF [44] recursively propagate embeddings on the graph, so as to encode collaborative signals along high-order connectivity into representations of users and items and empirically yield better representations [36].
- **Social Recommendation:** Social networks represent social relations among users, with connected users influencing each other. Recent works like DANSER [40], GraphRec [9], and DiffNet [39] employ GNNs to simulate such social influence modeling — propagating similar interests along high-order social connections — for better social recommendation.
- **Sequential Recommendation:** Historical session sequences of user behaviors are reorganized as a session graph, indicating transitions of items. Recently proposed works such as DGRec [25] and SR-GNN [41] conduct information propagation on such graph to model the dynamic user preference in that session.
- **Knowledge Graph-based Recommendation:** External item knowledge, such as commonsense knowledge and item attributes, can be well presented as knowledge graph [4, 37] (also well known as heterogeneous information network), where real-world entities and relationships are represented as subject-property-object triple facts. Wherein, multi-hop relational paths serve as the support evidence of user preferences on unseen interactions. Recent efforts like KGAT [32], KGCN [31], and KGNN-LS [30] utilize GNNs to synthesize information from such connectivity, strengthening representation ability, and enriching the relationships between a user and an item.

By introducing this emerging and promising topic, we expect the tutorial to facilitate researchers and practitioners in getting deep understanding and accurate insight on the topic, exchanging fruitful ideas, and promoting the developments of technologies.

2 CONTENT AND SCHEDULE

The tutorial is organized into three parts, in order to highlight formal analysis of graph-based recommendations interleaved with distinctions from traditional methods and discussions of experimental outcomes. In Parts I and II, we present preliminaries of recommender systems, introducing the problem formulation and the common paradigm. Parts III and IV are targeted at introducing the early technology of graph analysis and graph learning, *i.e.,* random walk and network embedding, and some representative works. In Part V, we revisit several common recommendation tasks — collaborative filtering, social recommendation, sequential recommendation, and knowledge graph-based recommendation — from the viewpoint of graph learning and reasoning. Here we highlight the recent success of GNN-based recommenders and discuss the future directions. The outline of the proposed tutorial is summarized in Table 1.

3 AUDIENCES

The proposed tutorial targets a broad audience comprising of both researchers and practitioners interested in recommender systems, information retrieval, data mining, and web search. We also introduce established methods tailored to different real-world scenarios, such as social recommendation and sequential recommendation, thereby targeting on industrial persons. For prerequisite, basic background of recommendation systems and graph learning will be preferred, but we will introduce the basic concepts of these two areas in the tutorial.

4 RELATED TUTORIALS

This is the second edition of the Tutorial on Learning and Reasoning on Graph for Recommendation. Prior to this, we presented the

Table 1: Outline of the tutorial.

Part I: Introduction
1.1 Personalized Recommendation
1.2 Organization of the tutorial
Part II: Preliminary of Recommendation
2. Problem Formulation
3. Unified View for Recommendation Paradigm
4. Limitations of Previous Works
Part III: Random Walk for Recommendation
5. Random Walk
6. Recent Works
Part IV: Network Embedding for Recommendation
5. Network Embedding
6. Recent Works
Part V: Graph Neural Networks for Recommendation
7. Collaborative Filtering
7.1 User-Item Bipartite Graph
7.2 Recent Works
8. Social Recommendation
8.1 Social Networks
8.2 Recent Works
9. Sequential Recommendation
9.1 Session Graphs
9.2 Recent Works
10. Knowledge Graph-based Recommendation
10.1 Collaborative Knowledge Graph
10.2 Recent Works

tutorial on CIKM'2019 [33]. Moreover, several wonderful tutorials were given at related conferences, including but are not limited to:

- Jun Xu, Xiangnan He, and Hang Li; Deep Learning for Matching in Search and Recommendation, at SIGIR 2018;
- William Hamilton, Rex Ying, Jure Leskovec, and Rok Sosic; Representation Learning on Networks, at WWW 2018;
- Jie Tang and Yuxiao Dong; Representation Learning on Networks, at WWW 2019;
- William Hamilton and Jian Tang; Graph Representation Learning, at AAAI 2019.

This proposed tutorial is significantly different from the previous tutorials in the sense that it focuses on recommendation technologies based on graph learning and reasoning.

5 PRESENTERS' BIOGRAPHY

Dr. Xiang Wang is a research fellow with School of Computing, National University of Singapore (NUS). He received his Ph.D. in Computer Science from NUS in 2019. His research interests cover recommender system, information retrieval, and data mining. He has over 20 publications in top conferences, such as SIGIR, KDD, WWW, and AAAI, and journals including TOIS and TKDE. He has served as the local chair of CCIS 2019, PC member of top-tier conferences including WWW, SIGIR, CIKM, and MM, and the regular reviewer for prestigious journals like TKDE and TOIS. He has presented the tutorial on "Learning and Reasoning on Graph for Recommendation" in CIKM 2019.

Dr. Xiangnan He is a professor with the University of Science and Technology of China (USTC). He received the Ph.D. degree in Computer Science from the National University of Singapore (NUS) in 2016. His research interests span information retrieval, data mining, and applied machine learning. He has over 60 publications appeared in top conferences such as SIGIR, WWW, KDD and MM, and journals including TKDE, TOIS, and TNNLS. His work on recommender systems has received the Best Paper Award Honourable Mention in WWW 2018 and SIGIR 2016. Moreover, he has served as the PC chair of CCIS 2019, area chair of MM 2019 and CIKM 2019, and PC member for several top conferences including SIGIR, WWW, KDD etc., as well as regular reviewer for journals including TKDE, TOIS, TMM, etc. He has rich teaching experience, including presenting the tutorial on "Deep Learning for Matching in Search and Recommendation" in WWW 2018 and SIGIR 2018, the tutorial on "Information Discovery in E-commerce" in SIGIR 2018, and the tutorial on "Recommendation Technologies for Multimedia Content" in ICMR 2018.

Dr. Tat-Seng Chua is the KITHCT Chair Professor at the School of Computing, National University of Singapore. He holds a Ph.D. from the University of Leeds, UK. He was the Acting and Founding Dean of the School from 1998-2000. Dr Chua's main research interest is in multimedia information retrieval and social media analytics. In particular, his research focuses on the extraction, retrieval and question-answering (QA) of text and rich media arising from the Web and multiple social networks. He is the co-Director of NExT, a joint Center between NUS and Tsinghua University to develop technologies for live social media search. Dr Chua is the 2015 winner of the prestigious ACM SIGMM award for Outstanding Technical Contributions to Multimedia Computing, Communications and Applications. He is the Chair of steering committee of ACM International Conference on Multimedia Retrieval (ICMR) and Multimedia Modeling (MMM) conference series. Dr Chua is also the General Co-Chair of ACM Multimedia 2005, ACM CIVR 2005, ACM SIGIR 2008, and ACM Web Science 2015. He serves in the editorial boards of four international journals. Dr. Chua is the co-Founder of two technology startup companies in Singapore.

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