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 performing prediction based on the "information isolated island". Such methods, however, overlook the relations among data instances, which may result in suboptimal performance especially for sparse scenarios. Moreover, the models built on a separate data instance only can hardly exhibit the reasons behind a recommendation, making the recommendation process opaque to understand.

In this tutorial, we revisit the recommendation problem from the perspective of graph learning. Common data sources for recommendation can be organized into graphs, such as user-item interactions (bipartite graphs), social networks, item knowledge graphs (heterogeneous graphs), among others. Such a graph-based organization connects the isolated data instances, bringing benefits to exploiting high-order connectivities that encode meaningful patterns for collaborative filtering, content-based filtering, social influence modeling and knowledge-aware reasoning. Together with the recent success of graph neural networks (GNNs), graph-based models have exhibited the potential to be the technologies for next-generation recommendation systems. This tutorial provides a review on graph-based learning methods for recommendation, with special focus on recent developments of GNNs and knowledge graph-enhanced recommendation. 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

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 [3, 4, 6, 7] 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) constructing predictive models to perform prediction based on the instances. These methods have achieved great success and been widely deployed in industry.

Nevertheless, the adoption of **information isolated island** in such paradigm — modeling each user-item interaction as an independent instance — overlooks the relations among instances, which might result in suboptimal performance [11, 12, 16]. 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 black-box nature makes the decision-making process opaque to understand and hamper 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. Recent years have witnessed a tremendous interest in graph neural networks (GNNs) [2, 5, 10]. 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. 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 interactions are organized as a bipartite graph between user and item nodes. Recent efforts like GC-MC [9] and NGCF [12] 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 [12].
- **Social Recommendation:** Social networks represent social relations among users, with connected users influencing each other. Recent works like DANSER [14], GraphRec [1], and DiffNet [13] 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 [8] and SR-GNN [15] 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 (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 [11] 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 RELATED TUTORIALS

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;
- Jie Tang and Yuxiao Dong; Representation Learning on Networks, at WWW 2019.

3 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 SIGIR, CIKM, and MM, and the regular reviewer for prestigious journals like TKDE and TOIS.

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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REFERENCES

[1] Wenqi Fan, Yao Ma, Qing Li, Yuan He, Yihong Eric Zhao, Jiliang Tang, and Dawei Yin. 2019. Graph Neural Networks for Social Recommendation. In *WWW*. 417–426.
[2] William L. Hamilton, Zhitao Ying, and Jure Leskovec. 2017. Inductive Representation Learning on Large Graphs. In *NeurIPS*. 1025–1035.
[3] Xiangnan He and Tat-Seng Chua. 2017. Neural Factorization Machines for Sparse Predictive Analytics. In *SIGIR*. 355–364.
[4] Xiangnan He, Lizi Liao, Hanwang Zhang, Liqiang Nie, Xia Hu, and Tat-Seng Chua. 2017. Neural Collaborative Filtering. In *WWW*. 173–182.
[5] Thomas N. Kipf and Max Welling. 2017. Semi-Supervised Classification with Graph Convolutional Networks. In *ICLR*.
[6] Steffen Rendle, Christoph Freudenthaler, Zeno Gantner, and Lars Schmidt-Thieme. 2009. BPR: Bayesian Personalized Ranking from Implicit Feedback. In *UAI*. 452–461.
[7] Steffen Rendle, Zeno Gantner, Christoph Freudenthaler, and Lars Schmidt-Thieme. 2011. Fast context-aware recommendations with factorization machines. In *SIGIR*. 635–644.
[8] Weiping Song, Zhiping Xiao, Yifan Wang, Laurent Charlin, Ming Zhang, and Jian Tang. 2019. Session-Based Social Recommendation via Dynamic Graph Attention Networks. In *WSDM*. 555–563.
[9] Rianne van den Berg, Thomas N. Kipf, and Max Welling. 2017. Graph Convolutional Matrix Completion. In *KDD*.
[10] Petar Velickovic, Guillem Cucurull, Arantxa Casanova, Adriana Romero, Pietro Liò, and Yoshua Bengio. 2018. Graph Attention Networks. In *ICLR*.
[11] Xiang Wang, Xiangnan He, Yixin Cao, Meng Liu, and Tat-Seng Chua. 2019. KGAT: Knowledge Graph Attention Network for Recommendation. In *KDD*. 950–958.
[12] Xiang Wang, Xiangnan He, Meng Wang, Fuli Feng, and Tat-Seng Chua. 2019. Neural Graph Collaborative Filtering. In *SIGIR*. 165–174.
[13] Le Wu, Peijie Sun, Yanjie Fu, Richang Hong, Xiting Wang, and Meng Wang. 2019. A Neural Influence Diffusion Model for Social Recommendation. In *SIGIR*.
[14] Qitian Wu, Hengrui Zhang, Xiaofeng Gao, Peng He, Paul Weng, Han Gao, and Guihai Chen. 2019. Dual Graph Attention Networks for Deep Latent Representation of Multifaceted Social Effects in Recommender Systems. In *WWW*. 2091–2102.
[15] Shu Wu, Yuyuan Tang, Yanqiao Zhu, Liang Wang, Xing Xie, and Tieniu Tan. 2019. Session-based Recommendation with Graph Neural Networks. In *AAAI*.
[16] Fuzheng Zhang, Nicholas Jing Yuan, Defu Lian, Xing Xie, and Wei-Ying Ma. 2016. Collaborative Knowledge Base Embedding for Recommender Systems. In *KDD*. 353–362.