Graph Neural Networks for Recommender System

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ABSTRACT

Recently, graph neural network (GNN) has become the new state-of-the-art approach in many recommendation problems, with its strong ability to handle structured data and to explore high-order information. However, as the recommendation tasks are diverse and various in the real world, it is quite challenging to design proper GNN methods for specific problems. In this tutorial, we focus on the critical challenges of GNN-based recommendation and the potential solutions. Specifically, we start from an extensive background of recommender systems and graph neural networks. Then we fully discuss why GNNs are required in recommender systems and the four parts of challenges, including graph construction, network design, optimization, and computation efficiency. Then, we discuss how to address these challenges by elaborating on the recent advances of GNN-based recommendation models, with a systematic taxonomy from four critical perspectives: stages, scenarios, objectives, and applications. Last, we finalize this tutorial with conclusions and discuss important future directions.

CCS CONCEPTS

• **Information systems → Information retrieval**.

KEYWORDS

Recommender System, Graph Neural Network

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1 INTRODUCTION

With the rapid explosion of information on various services and platforms (*e.g.*, E-commerce, short videos, etc.), personalized recommender systems which aim to alleviate the problem of information overload, are developing fast and widely deployed. Driven by its effectiveness in the real world, both industrial and academia pay much attention to this area, prompting increasing publications, workshops, and tutorials.

The development of recommender systems generally includes three stages, shallow models [16, 18], neural network (NN) -based models [9, 11, 13], and GNN-based models [2, 7, 12, 21]. In recent years, GNN has attracted more and more attention in various cutting-edge fields [1, 2, 8, 17, 19, 21]. For recommender systems, GNN has the natural ability to establish correlations among users, items, and associated features through conducting information propagation on graphs. Specifically, neighborhood embeddings are aggregated to the target node/edge, and this operation will be performed several times. In this way, high-order structured information and multi-hop relevance among graph entities (nodes or edges) are encoded in corresponding embeddings. Thanks to the powerful modeling ability, GNN has achieved groundbreaking performance and becomes state-of-the-art models in recommender systems [12, 14, 21, 23, 24].

GNNs' specific advantages in recommender systems are as follows. The first one is the unifying structured data. In recommender systems, the data is in different forms, and the graph is powerful to organize and unify them with nodes and edges representing various entities or features. In this way, specially designed GNN will capture correlations and interplay among different data sources and learn high-level representations for specific tasks. The second advantage is the modeling of high-order connectivity. Multiple layers of embedding propagation on graphs can relate multi-hop entity information, then high-order connectivity and similarity among users and items will be captured. The last advantage is the multiple supervision signals. GNN can alleviate the problem of data sparsity in recommender systems with semi-supervised signals, such as assisting in modeling the target behaviors with other behaviors in multi-behavior recommendation [15]. Moreover, the self-supervised paradigm is also useful in GNN-based models [22].

Despite the effectiveness of GNN, there are essential challenges in designing GNN-based recommendation models. To be more specific, the challenges include: 1) graph construction: constructing proper graph nodes and edges; 2) network design: designing effective GNN architectures with proper embedding propagation/aggregation layers; 3) model optimization: designing suitable optimization goal, loss function, data sampling manner, etc.; 4) computation efficiency: ensuring efficient training and inference of the recommendation model. To summarize existing works about GNN for recommendation, we categorize them from four different perspectives, including stage, scenario, objective, and application.

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In detail, the stage follows a pipeline of matching, ranking, and re-ranking. The scenario consists of social [24], sequential [4], session-based [5], cross-domain [10], multi-behavior [15], bundle recommendation [3], etc. The objectives mainly contain accuracy, and at the same time, diversity [25], explainability [20], and fairness [6] attract much attention as well. The application widely ranges from product, Point-of-Interest, movie, video, news, etc. Besides, there are still many unresolved issues in GNN-based recommendation models, including network depth, computation efficiency for large-scale graphs, sub-optimal modeling of dynamic data, etc.

In this tutorial, we will systematically discuss the challenges, methods, and directions of GNN-based recommendation models, while carefully elaborating on existing works. We expect this tutorial to facilitate the attendees in getting a deep understanding of 1) why GNN is effective for recommendation, 2) what kinds of critical challenges exist, 3) and how the existing works address them, and 4) insightful and promising future research directions. The authors have released a survey [7] on graph neural network-based recommender system, which can also benefit the attendees.

2 RELATED TUTORIALS AT RELATED CONFERENCES

There are two related tutorials (both of each have been held twice) as follows. The first one is about deep learning for recommendation, of which GNN-based recommendation was simply mentioned. The second one is about learning and reasoning in graph-based recommendation, which paid much attention to traditional graph embedding models and did not fully discuss GNN-based recommendation. Therefore, to the best of our knowledge, this tutorial will be the first systematic tutorial for GNN-based recommendation.

- **Deep Learning for Recommendations: Fundamentals and Advances, TheWebConf 2021 and IJCAI 2021**
  Difference. This tutorial introduced several mainstream directions of applying deep learning (DL) technologies to recommender systems, including reinforcement Learning (RL), graph neural networks (GNN), automated machine learning (AutoML), and adversarial attacks. By contrast, we will focus on GNN for recommendation. Specifically, we present a comprehensive understanding of challenges when using the GNN framework for various recommendation problems, and correspondingly summarize the methods addressing relevant issues. Moreover, we will cover more recently published works, and elaborate on insightful future directions on this field.
- **Learning and Reasoning on Graph for Recommendation, WSDM 2020 and CIKM 2019**
  Difference. This tutorial introduced graph technologies applied to recommender systems, including random work, network embedding, and GNNs. In addition, the GNN part only introduced several works. By contrast, we will focus on GNN-based recommender systems, involving various cutting-edge research problems. Besides, we will provide a systematic taxonomy for existing works from four aspects, *i.e.*, stage, scenario, objective, and application. Moreover, we will also provide a thorough elaboration on challenges and how to address them when designing GNN-based recommendation models, which is totally ignored by this tutorial but very important to the attendees.

3 FORMAT AND DETAILED SCHEDULE

This tutorial is organized into five parts. In Part I, we present preliminaries of recommender systems and graph neural networks, with the problem formulation and the common paradigms. In Part II we target at explaining why GNNs are required in recommender systems. In Part III, we present the four folds of challenges for GNN-based recommender systems. In Part IV, we discuss how to address the challenges by elaborating on the recent advances. In Part V, we conclude this tutorial and discuss the open problems in GNN-based recommendation and important future directions. The outline of the tutorial is summarized as follows.

(1) **Part I: Background**
  - Recommender System
  - Graph Neural Networks

(2) **Part II: Why GNNs Are Required in Recommender Systems**

(3) **Part III: Challenges for GNN-based Recommendation**
  - Graph Construction
  - Network Design
  - Model Optimization
  - Computation Efficiency

(4) **Part IV: Advances of GNN-based Recommender Systems**
  - GNN in Different Stages of Recommender System
  - GNN for Different Objectives of Recommender System
  - GNN in Different Scenarios of Recommender System
  - GNN in Different Applications of Recommender System

(5) **Part V: Conclusion and Open Discussions**

4 TYPE OF SUPPORT MATERIALS TO BE SUPPLIED TO ATTENDEES

The support materials which can well benefit the attendees are as follows.

- Website: we build a website (https://sites.google.com/view/gnn-recsys) which contains the detailed information of this tutorial.
- Slides: we will offer our materials to tutorial attendees; besides, slides will be released publicly.
- Related Papers: important related papers will be systematically listed in the website.
- Survey: The authors have released a survey [7] on graph neural network-based recommender system, which can benefit the attendees.

5 BIOGRAPHY OF PRESENTERS

- **Dr. Chen Gao** is now a Postdoc Researcher with the Department of Electronic Engineering, Tsinghua University. He obtained his Ph.D. Degree and Bachelor Degree from the same department in 2021 and 2016, respectively. His research mainly focuses on recommender system. He has over 30 publications in conferences and journals such as SIGIR, WWW, ICLR, KDD, IJCAI, TKDE, TKDD, etc. He serves as the PC member of conferences including WSDM, WWW, CIKM, ICLR, NeurIPS, etc. His work on graph neural network-based bundle recommendation received the Best Short Paper Honorable Mention Award in SIGIR 2020. He is also selected as Top 100 Chinese New Stars in Artificial

Intelligence (Data Mining Area) by Baidu Scholar. He has organized and presented the tutorial on "Advances in Recommender System" in KDD 2020 and the tutorial on "Towards Automated Recommender System" in IJCAI 2021.

- **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 30 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 and WSDM 2020, and the tutorial on "Bias Issues and Solutions in Recommender System" in WWW 2021.
- **Dr. Xiangnan He** is a professor with the University of Science and Technology of China. He received the Ph.D. degree in Computer Science from the National University of Singapore in 2016. His research interests span information retrieval and data mining, with over 60 publications appeared in top conferences such as SIGIR, WWW, and KDD, and journals including TKDE, TOIS, and TNNLS. His works on recommender systems have received the Best Paper Award Honorable Mention in SIGIR 2021, WWW 2018, and SIGIR 2016. He has rich teaching experience, especially for presenting tutorials: "Conversational Recommendation: Formulation, Methods, and Evaluation" in SIGIR 2020, "Deep Learning for Matching in Search and Recommendation" in WWW 2018 and SIGIR 2018, "Information Discovery in E-commerce" in SIGIR 2018, and "Recommendation Technologies for Multimedia Content" in ICMR 2018.
- **Dr. Yong Li** is currently a Tenured Associate Professor of the Department of EE, Tsinghua University. He received the Ph.D. degree in Electronic Engineering from Tsinghua University in 2012. His research interests include data mining and machine learning. He serves as (S)PC of major DM/AI conferences, including KDD, WWW, IJCAI, AAAI, SIGIR, and UbiComp. He has published over 100 papers on first-tier conferences and journals, including KDD, WWW, NeurIPS, ICLR, SIGIR, etc. He has rich teaching experience, including teaching two classes "Mobile Data Mining" and "Big Data Technology and Application" at Tsinghua University for years, presenting the tutorial on "Smartphone App Usage Understanding, Modeling, and Prediction" in UbiComp 2019, the tutorial on "Advances in Recommender System" in KDD 2020 and the tutorial on "Towards Automated Recommender System" in IJCAI 2021.

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