Graph Data Mining in Recommender Systems

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Abstract. With the rapid development of e-commerce, massive data is generated from various e-commerce platforms. Most of the generated data can be represented in the forms of graph, which is capable to demonstrate the complicated relations among various entities, for example, graphs describe the interactions history between users and items. It is critical for the platforms to mine graph data to formulate recommendation strategy to gain more profits. For instance, in a user-item interaction graph, we can utilize graph data mining techniques to capture users' behavioral patterns to make personalized recommendation strategies. Graph data mining in recommendation is currently a research topic attracts more and more attentions from industry and academic fields. In this half-day tutorial, we will present some key graph data mining methods and its applications in recommendation. We hope to find out the directions for the future work and that more theoretical models can be applied under real-world scenarios.

Keywords: Graph data mining · Recommender systems · Graph neural networks · Explainable machine learning · Self-supervised learning.

1 Target Audience, Prerequisites, and Benefits

- **Prerequisites.** This tutorial is aimed at algorithm designers and practitioners interested in graph data mining and recommendation and academic researchers in these domains. The audiences' acquaintance should cover basic knowledge of graph data, machine learning, and recommender systems.
- **Benefits.** After the tutorial, we expect that the attendees could 1) gain a high-level understanding of the overview of graph mining for recommendation, 2) know some key concepts in the above topics, 3) get familiar to some state-of-the-art graph-based recommendations.

1.1 Significance

Graph-based data mining approaches [5,11,18] have caught much attention since graphs can capture complicated relation among data (nodes and edges). These graph-based methods have shown promise for some real scenarios thanks to the graph data structure, like natural language processing [11], healthcare [18], recommendation [5] and so on. For recommendation, traditional approaches mostly focus on the features of users and items, and the users and items' matrix transformation [7]. However, they ignore the potential graph-like relation among users and items. For example, adjacent nodes in recommendation graph may represent similar meaning, and diverse paths on graph tend to display specific relations among nodes. Therefore, in order to capture the above relations, some recent recommendations model the data to graph structures.

Although there were some related forums discussing graph-based recommendation in recent years, ours are different from them, and we add some state-of-the-art graph-based recommendations. Our tutorial mainly includes three parts, graph representation learning and its application for recommendations, graph-based explainable recommendations, and graph contrastive learning and future application in recommendation. Details are shown in Section 2.

1.2 Relevance

As can been seen in the reference list, the tutorial will summary and categorize the graph-based data mining for recommendation approaches in the last ten years. Therefore, this topic is perfectly suitable for The Conference on Information and Knowledge Management (CIKM), which is one of the top forums of research on data science and knowledge management in the world. Specifically, the main topic conforms the area of "Neural Information and Knowledge Processing". Since we will introduce knowledge-aware recommendation, our content also meets the area "Integration and Aggregation".

2 Outline

The tutorial contains three main parts, graph representation learning and its application in recommendation, reasoning for graph-based recommendation, and graph contrastive learning and promising future application in recommendation.

- **Graph Representation Learning in General and Its Application in Recommendation. (60 min)**
  1. Graph Representation Learning in General. (30 mins)
  2. When Graph Meets Recommender Systems. (30 mins)
- **Reasoning for Graph-based Recommendation. (60 min)**
  1. Reasoning is Important for Graph-based Recommendation. (10 min)
  2. Explainable Recommendations via Graph Modelling. (40 min)
  3. Conclusion and Future Directions. (10 min)
- **Graph Contrastive Learning for Recommendation. (60 min)**
  1. Introduction to Contrastive Learning. (10 min)
  2. Introduction to Graph Contrastive Learning. (20 min)
  3. Applications of Graph Contrastive Learning in Recommendation. (30 min)

3 Important References

3.1 Related tutorials

Some closely related tutorials were presented in some forums. We will list some of them here and give short introductions for them:

- The 13th ACM International WSDM Conference, in Houston, Texas, February 3-7 2020. **Learning and Reasoning on Graph for Recommendation**[1]. This tutorial mainly focus on graph based recommendations, giving details about traditional graph data mining techniques more than sole GNNs based methods. Our proposed tutorial takes the scenario-specific taxonomy to introduce different graph mining techniques and their applications in recommendation. Moreover, we will introduce more up-to-date methods, including graph contrastive learning [14], to further enrich audiences' knowledge about this domain.
- International Joint Conference on Artificial Intelligence - Pacific Rim International Conference on Artificial Intelligence 2020, in Yokohama, Japan, January 8 2021. **Next-Generation Recommender Systems and Their Advanced Applications**[2]. This tutorial introduce the next-generation recommender systems from three aspects: session-based recommendation, graph based recommendation, interactive and conversation based recommendation, in a scenario-specific manner. However, our proposed tutorial will introduce related knowledge from different aspects: general graph learning methods, reasoning for graph based recommendation, and contrastive learning for recommendation.
- The Web Conference 2021, in Ljubljana, Slovenia, April 17 2021. **Deep Recommender System: Fundamentals and Advances**[3]. This tutorial systematically introduced deep recommendation systems from multiple aspects. One related aspect is the introduction to GNNs based recommendation systems. Comparing to our proposed tutorial, we both emphasize the roles of GNNs in recommendation. However, we pay more attentions to their application scenarios.

3.2 Related Literature

- Survey papers [1, 9, 19].
- Graph random walk and its applications in recommender systems [3, 12, 13].
- Graph embedding and its applications in recommender systems [2, 4, 15, 21].
- Graph neural networks and its applications in recommender systems [6, 8, 16, 22].
- Graph contrastive learning [14, 17, 23].
- Contrastive learning in recommendation [10, 20]

[1] https://next-nus.github.io/
[2] https://sites.google.com/view/shoujinwanghome/home/talks/ijcai-pricai-2020-tutorial
[3] https://deeprs-tutorial.github.io/

4 Bios of Presenters

- **Hongxu Chen** is a Data Scientist, now working as a Postdoctoral Research Fellow in School of Computer Science at University of Technology Sydney, Australia. He obtained his Ph.D. in Computer Science at The University of Queensland in 2020. His research interests mainly focus on data science in general and expend across multiple practical application scenarios, such as network science, data mining, recommendation systems and social network analytics. In particular, his research is focusing on learning representations for information networks and applying the learned network representations to solve real-world problems in complex networks such as biology, e-commerce and social networks, financial market and recommendations systems with heterogeneous information sources. He has published many peer-reviewed papers in top-tier high-quality international conferences and journals, such as SIGKDD, ICDE, ICDM, AAAI, IJCAI, TKDE. He also serves as program committee member and reviewers in multiple international conference, such as CIKM, ICDM, KDD, SIGIR, AAAI, PAKDD, WISE, and he also acts as invited reviewer for multiple journals in his research fields, including Transactions on Knowledge and Data Engineering (TKDE), WWW Journal, VLDB Journal, IEEE Transactions on Systems, Man and Cybernetics: Systems, Journal of Complexity, ACM Transactions on Data Science, Journal of Computer Science and Technology.
- **Yicong Li** is currently a PhD student of Data Science and Machine Intelligence (DSMI) Lab of Advanced Analytics Institute, University of Technology Sydney. She obtained her Master's degree from National University of Defense Technology in 2019. Her research interests mainly focus on data science, graph neural networks, recommender systems, natural language processing and so on. In particular, her current research is focusing on the explainable machine learning, especially the application in recommendation area. She has published papers in international conferences and journals, such as WSDM, KSEM and IEEE Access. She have also reviewed submitted papers in many top-tier conferences and journals, like AAAI, KDD, WWW, IJCAI, WSDM, ICONIP and so on. In addition, she has been invited to review manuscripts in IEEE Transactions on Neural Networks and Learning Systems (TNNLS), which is a top-tier journal in artificial intelligence.
- **Haoran Yang** is currently a Ph.D. student of Data Science and Machine Intelligence (DSMI) Lab under Advanced Analytics Institute, University of Technology Sydney. He obtained his B.Sc. from Nanjing University in 2020. His research interests include but not limited to data mining, graph neural networks, and recommender systems. Haoran's PhD research mainly focuses on formulating efficient graph neural networks and applying them in real-world problems. He had published a paper in top-tier data mining conference, ICDM. And he was invited to serve as a reviewer in CIKM.

References

1. Cai, H., Zheng, V.W., Chang, K.C.C.: A comprehensive survey of graph embedding: Problems, techniques, and applications. IEEE Transactions on Knowledge and Data Engineering **30**(9), 1616–1637 (2018). https://doi.org/10.1109/TKDE.2018.2807452
2. Chen, C., Tsai, M., Lin, Y., Yang, Y.: Query-based music recommendations via preference embedding. In: Sen, S., Geyer, W., Freyne, J., Castells, P. (eds.) Proceedings of the 10th ACM Conference on Recommender Systems, Boston, MA, USA, September 15-19, 2016. pp. 79–82. ACM (2016). https://doi.org/10.1145/2959100.2959169, https://doi.org/10.1145/2959100.2959169
3. Cooper, C., Lee, S.H., Radzik, T., Siantos, Y.: Random walks in recommender systems: Exact computation and simulations. In: Proceedings of the 23rd International Conference on World Wide Web. p. 811–816. WWW '14 Companion, Association for Computing Machinery, New York, NY, USA (2014). https://doi.org/10.1145/2567948.2579244, https://doi.org/10.1145/2567948.2579244
4. Grover, A., Leskovec, J.: node2vec: Scalable feature learning for networks. In: Krishnapuram, B., Shah, M., Smola, A.J., Aggarwal, C.C., Shen, D., Rastogi, R. (eds.) Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, August 13-17, 2016. pp. 855–864. ACM (2016). https://doi.org/10.1145/2939672.2939754, https://doi.org/10.1145/2939672.2939754
5. Guo, Q., Zhuang, F., Qin, C., Zhu, H., Xie, X., Xiong, H., He, Q.: A survey on knowledge graph-based recommender systems. IEEE Transactions on Knowledge and Data Engineering (2020)
6. Hamilton, W.L., Ying, Z., Leskovec, J.: Inductive representation learning on large graphs. In: Guyon, I., von Luxburg, U., Bengio, S., Wallach, H.M., Fergus, R., Vishwanathan, S.V.N., Garnett, R. (eds.) Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA. pp. 1024–1034 (2017), https://proceedings.neurips.cc/paper/2017/hash/5dd9db5e033da9c6fb5ba83c7a7ebea9-Abstract.html
7. He, X., Chua, T.S.: Neural factorization machines for sparse predictive analytics. In: Proceedings of the 40th International ACM SIGIR conference on Research and Development in Information Retrieval. pp. 355–364 (2017)
8. Kipf, T.N., Welling, M.: Semi-supervised classification with graph convolutional networks. In: 5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings. OpenReview.net (2017), https://openreview.net/forum?id=SJU4ayYgl
9. Liu, J., Duan, L.: A survey on knowledge graph-based recommender systems. In: 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC). vol. 5, pp. 2450–2453 (2021). https://doi.org/10.1109/IAEAC50856.2021.9390863
10. Liu, Z., Ma, Y., Ouyang, Y., Xiong, Z.: Contrastive learning for recommender system. CoRR **abs/2101.01317** (2021), https://arxiv.org/abs/2101.01317
11. Nastase, V., Mihalcea, R., Radev, D.R.: A survey of graphs in natural language processing. Natural Language Engineering **21**(5), 665–698 (2015)

12. Nikolakopoulos, A.N., Karypis, G.: Recwalk: Nearly uncoupled random walks for top-n recommendation. In: Culpepper, J.S., Moffat, A., Bennett, P.N., Lerman, K. (eds.) Proceedings of the Twelfth ACM International Conference on Web Search and Data Mining, WSDM 2019, Melbourne, VIC, Australia, February 11-15, 2019. pp. 150–158. ACM (2019). https://doi.org/10.1145/3289600.3291016, https://doi.org/10.1145/3289600.3291016
13. Perozzi, B., Al-Rfou, R., Skiena, S.: Deepwalk: online learning of social representations. In: Macskassy, S.A., Perlich, C., Leskovec, J., Wang, W., Ghani, R. (eds.) The 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '14, New York, NY, USA - August 24 - 27, 2014. pp. 701–710. ACM (2014). https://doi.org/10.1145/2623330.2623732, https://doi.org/10.1145/2623330.2623732
14. Qiu, J., Chen, Q., Dong, Y., Zhang, J., Yang, H., Ding, M., Wang, K., Tang, J.: GCC: graph contrastive coding for graph neural network pre-training. In: Gupta, R., Liu, Y., Tang, J., Prakash, B.A. (eds.) KDD '20: The 26th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, Virtual Event, CA, USA, August 23-27, 2020. pp. 1150–1160. ACM (2020). https://doi.org/10.1145/3394486.3403168, https://doi.org/10.1145/3394486.3403168
15. Tang, J., Qu, M., Wang, M., Zhang, M., Yan, J., Mei, Q.: LINE: large-scale information network embedding. In: Gangemi, A., Leonardi, S., Panconesi, A. (eds.) Proceedings of the 24th International Conference on World Wide Web, WWW 2015, Florence, Italy, May 18-22, 2015. pp. 1067–1077. ACM (2015). https://doi.org/10.1145/2736277.2741093, https://doi.org/10.1145/2736277.2741093
16. Velickovic, P., Cucurull, G., Casanova, A., Romero, A., Liò, P., Bengio, Y.: Graph attention networks. In: 6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings. OpenReview.net (2018), https://openreview.net/forum?id=rJXMpikCZ
17. Velickovic, P., Fedus, W., Hamilton, W.L., Liò, P., Bengio, Y., Hjelm, R.D.: Deep graph infomax. CoRR **abs/1809.10341** (2018), http://arxiv.org/abs/1809.10341
18. Wang, F., Cui, P., Pei, J., Song, Y., Zang, C.: Recent advances on graph analytics and its applications in healthcare. In: Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. pp. 3545–3546 (2020)
19. Wu, S., Zhang, W., Sun, F., Cui, B.: Graph neural networks in recommender systems: A survey. CoRR **abs/2011.02260** (2020), https://arxiv.org/abs/2011.02260
20. Xie, X., Sun, F., Liu, Z., Gao, J., Ding, B., Cui, B.: Contrastive pre-training for sequential recommendation. CoRR **abs/2010.14395** (2020), https://arxiv.org/abs/2010.14395
21. Yang, J., Chen, C., Wang, C., Tsai, M.: Hop-rec: high-order proximity for implicit recommendation. In: Pera, S., Ekstrand, M.D., Amatriain, X., O'Donovan, J. (eds.) Proceedings of the 12th ACM Conference on Recommender Systems, RecSys 2018, Vancouver, BC, Canada, October 2-7, 2018. pp. 140–144. ACM (2018). https://doi.org/10.1145/3240323.3240381, https://doi.org/10.1145/3240323.3240381
22. Ying, R., He, R., Chen, K., Eksombatchai, P., Hamilton, W.L., Leskovec, J.: Graph convolutional neural networks for web-scale recommender systems. In: Guo, Y., Farooq, F. (eds.) Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, KDD 2018, London, UK, August

19-23, 2018. pp. 974–983. ACM (2018). https://doi.org/10.1145/3219819.3219890, https://doi.org/10.1145/3219819.3219890
23. You, Y., Chen, T., Sui, Y., Chen, T., Wang, Z., Shen, Y.: Graph contrastive learning with augmentations. In: Larochelle, H., Ranzato, M., Hadsell, R., Balcan, M., Lin, H. (eds.) Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual (2020), https://proceedings.neurips.cc/paper/2020/hash/3fe230348e9a12c13120749e3f9fa4cd-Abstract.html