Fair Graph Mining

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ABSTRACT

In today's increasingly connected world, graph mining plays a pivotal role in many real-world application domains, including social network analysis, recommendations, marketing and financial security. Tremendous efforts have been made to develop a wide range of computational models. However, recent studies have revealed that many widely-applied graph mining models could suffer from potential discrimination. Fairness on graph mining aims to develop strategies in order to mitigate bias introduced/amplified during the mining process. The unique challenges of enforcing fairness on graph mining include (1) theoretical challenge on non-IID nature of graph data, which may invalidate the basic assumption behind many existing studies in fair machine learning, and (2) algorithmic challenge on the dilemma of balancing model accuracy and fairness. This tutorial aims to (1) present a comprehensive review of state-of-the-art techniques in fairness on graph mining and (2) identify the open challenges and future trends. In particular, we start with reviewing the background, problem definitions, unique challenges and related problems; then we will focus on an in-depth overview of (1) recent techniques in enforcing group fairness, individual fairness and other fairness notions in the context of graph mining, and (2) future directions in studying algorithmic fairness on graphs. We believe this tutorial could be attractive to researchers and practitioners in areas including data mining, artificial intelligence, social science and beneficial to a plethora of real-world application domains.

CCS CONCEPTS

• Information systems → Data mining; **• Applied computing → Law, social and behavioral sciences**.

KEYWORDS

graph mining, algorithmic fairness, bias mitigation

ACM Reference Format:

Jian Kang and Hanghang Tong. 2021. Fair Graph Mining. In *Proceedings of the 30th ACM International Conference on Information and Knowledge Management (CIKM '21), November 1–5, 2021, Virtual Event, QLD, Australia.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3459637.3482030

CIKM '21, November 1–5, 2021, Virtual Event, QLD, Australia

ACM ISBN 978-1-4503-8446-9/21/11…$15.00
https://doi.org/10.1145/3459637.3482030

1 INTENDED AUDIENCE

The tutorial is designed for all researchers and practitioners in data mining, artificial intelligence, social science, as well as related areas. The audiences are assumed to have the basic knowledge on probability, linear algebra and machine learning. However, no prior knowledge on specific algorithms is required. This tutorial aims to achieve a good balance between the introductory and advanced materials. It is designed for 40% novice, 30% intermediate, 30% expert.

2 LENGTH OF TUTORIAL

The length of the tutorials will be half day, i.e., 3 hours plus breaks.

3 PRESENTER BIOGRAPHY

The presenters and contributors of this tutorial include Jian Kang and Hanghang Tong. Their biographies and expertises are listed here.

Jian Kang. He is currently a Ph.D. student in the Department of Computer Science at the University of Illinois at Urbana-Champaign. Prior to that, he was a Ph.D. student in the School of Computing, Informatics, and Decision Systems Engineering at Arizona State University. He received his M.CS. degree in Computer Science from the University of Virginia in 2016 and B.Eng. degree in Telecommunication Engineering from Beijing University of Posts and Telecommunications in 2014. His current research interests lie in large-scale data mining and machine learning, especially on graphs, with a focus on their algorithmic fairness. His research works on related topics have been published at several major conferences and journals in data mining and machine learning. He has also served as a reviewer and a program committee member in top-tier data mining and artificial intelligence venues and journals (e.g., NeurIPS, ICML, ICLR, CIKM, WSDM, JMLR, TKDE, etc). For more information, please refer to his personal website at http://jiank2.web.illinois.edu/.

Hanghang Tong. He is currently an associate professor at Department of Computer Science at University of Illinois at Urbana-Champaign. Before that he was an associate professor at School of Computing, Informatics, and Decision Systems Engineering (CIDSE), Arizona State University. He received his M.Sc. and Ph.D. degrees from Carnegie Mellon University in 2008 and 2009, both in Machine Learning. His research interest is in large scale data mining for graphs and multimedia. He has received several awards, including SDM/IBM Early Career Data Mining Research award (2018), NSF CAREER award (2017), ICDM 10-Year Highest Impact Paper award (2015), four best paper awards (TUP'14, CIKM'12, SDM'08, ICDM'06), seven 'bests of conference', 1 best demo, honorable mention (SIGMOD'17), and 1 best demo candidate, second place (CIKM'17). He has published over 200 refereed articles. He is the Editor-in-Chief of SIGKDD Explorations (ACM), and an associate editor of Knowledge and Information Systems (Springer) and Computing Surveys (ACM); and has served as a program committee member in multiple data mining, database and artificial intelligence venues (e.g., SIGKDD, CIKM, SIGMOD, AAAI, WWW, etc.). He has given several tutorials at top-tier conferences, such as IEEE Big Data 2015, SDM 2016, WSDM 2018, KDD 2018, CIKM 2020 (https://sites.google.com/view/cikm2020-tutorial-netalign/home), etc. For more information, please refere to his personal website at http://tonghanghang.org/.

4 OUTLINE OF TUTORIAL

- Introduction
  - Background and motivations
  - Problem definitions and settings
  - Key challenges
  - Related problems
- Part I: Group Fairness on Graphs
  - Fair graph ranking
  - Fair graph clustering
  - Fair graph embedding
- Part II: Individual Fairness on Graphs
  - Optimization-based methods
  - Ranking-based methods
- Part III: Beyond Group Fairness and Individual Fairness on Graphs
  - Rawlsian fairness
  - Degree-related fairness
  - Counterfactual fairness
- Part IV: Open Challenges and Future Directions
  - Fairness on dynamic graphs
  - Fairness on multi-network mining
  - Multi-resolution fairness on graphs
  - Connections between group fairness and individual fairness on graphs

5 DESCRIPTION OF TOPICS

5.1 Introduction

In this part, we start with the background and motivations of studying algorithmic fairness on graphs. Then we provide an overview of existing problem definitions and settings, along with the key challenges in solving algorithmic fairness problems in the context of graph mining. Finally, we briefly review problems that are closely related to fairness on graphs, including auditing [15, 31, 34], adversarial attack [7, 37, 38], privacy preservation [8, 30, 36], etc.

5.2 Part I: Group Fairness on Graphs

In this part, we will present the state-of-the-art techniques on enforcing grouping fairness on graph mining algorithms, which aims to achieve fairness among nodes of different demographic groups. We categorize the problem into the following scenarios. (1) *Graph ranking* is a fundamental task in graph mining that aims to measure importance of nodes in graph or proximity of nodes w.r.t. a query node. Group fairness on ranking aims to ensure that nodes in different demographic groups enjoy similar average rank or stationary probability mass. Representative works include [18, 29]. It should be noted that we will focus on graph-based ranking algorithms for link analysis (e.g., PageRank), instead of other commonly-used ranking methods (e.g., learning to rank). (2) *Graph clustering* aims to divide nodes into several clusters so that nodes within the same cluster are similar to each other. Group fairness on graph clustering aims to ensure nodes in the same demographic groups are evenly distributed among the clusters [17]. (3) *Graph embedding* attracts much research attention in recent years, which targets for learning high-dimensional latent representation for nodes. A node embedding satisfies group fairness if a balanced performance is achieved on downstream task(s) (e.g., node classification, link prediction) when using the embedding. Various methods have been proposed in this direction, including adversarial learning based approaches [2, 3, 6, 12, 21, 33], bayesian based approach [4], statistical based approaches [5, 16, 19, 23, 27, 35] and others [20, 22].

5.3 Part II: Individual Fairness on Graphs

In this part, we review recent efforts in enforcing individual fairness on graphs by following the principle of 'similar nodes receive similar algorithmic outcomes'. Existing methods in individually fair graph mining can be classified as (1) *optimization-based approaches* [13, 14, 19] which applies the Laplacian regularization on the mining results w.r.t. the graph Laplacian of node-node similarity matrix, and (2) *ranking-based approach* [9] which leverages learning-to-rank to calibrate the inconsistency between input space and output space in Laplacian regularization.

5.4 Part III: Beyond Group and Individual Fairness on Graphs

In this part, we will introduce three fairness notions other than extensively studied group fairness and individual fairness, and present how they are applied in fair graph learning. These notions include: (1) *rawlsian fairness*, which is a fairness notion originated in John Rawls' theory of distributive justice [26] and has been applied to guarantee fairness on influence maximization [10, 11, 24, 25] (2) *degree-related fairness*, which promises that nodes of different degrees will have comparable performance on downstream tasks (e.g., node classification) [28, 32], and (3) *counterfactual fairness*, where the learning outcomes are counterfactually fair w.r.t. sensitive attribute (i.e., being independent to the value of sensitive attribute) [1].

5.5 Part IV: Future Directions

In this part, we will point out open challenges in this field and share our thoughts regarding the future directions about fairness on graphs, including (1) *fairness on dynamic graphs* where bias mitigation algorithms can be developed to track the change in bias measurement and mitigate the bias efficiently in a dynamic environment, (2) *fairness on multi-network mining* where fairness should be guaranteed on multi-sourced networks instead of existing works on single network only, (3) *multi-resolution fairness on graphs* where a debias algorithm that applies on a coarse granularity (e.g., a subgraph) can also help mitigate the bias in a finer granularity (e.g., a subgraph within a subgraph), or vice versa, and (4) *connections between group fairness and individual fairness on graphs* where new theoretical analysis is needed to understand to what extent group fairness and individual fairness can be ensured simultaneously with certain condition(s).

6 COVERED WORKS

Due to the space limit, we only list some most relevant papers. Note that the following is not an exhaustive list of papers that are relevant to the topic.

- Part I: Group Fairness on Graphs
  - Graph ranking
    - Sotiris Tsioutsiouliklis, Evaggelia Pitoura, Panayiotis Tsaparas, Ilias Kleftakis, and Nikos Mamoulis. 2021. Fairness-Aware PageRank. In *Proceedings of the Web Conference 2021*. 3815–3826
  - Graph clustering
    - Matthäus Kleindessner, Samira Samadi, Pranjal Awasthi, and Jamie Morgenstern. 2019. Guarantees for spectral clustering with fairness constraints. In *International Conference on Machine Learning*. PMLR, 3458–3467.
  - Graph embedding
    - Avishek Bose and William Hamilton. 2019. Compositional fairness constraints for graph embeddings. In *International Conference on Machine Learning*. PMLR, 715–724.
    - Maarten Buyl and Tijl De Bie. 2020. DeBayes: a Bayesian method for debiasing network embeddings. In *International Conference on Machine Learning*. PMLR, 1220–1229.
    - Tahleen A Rahman, Bartlomiej Surma, Michael Backes, and Yang Zhang. 2019. Fairwalk: Towards Fair Graph Embedding. In *IJCAI*. 3289–3295.
- Part II: Individual Fairness on Graphs
  - Optimization based method
    - Jian Kang, Jingrui He, Ross Maciejewski, and Hanghang Tong. 2020. InFoRM: Individual Fairness on Graph Mining. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 379–389.
  - Ranking based method
    - Yushun Dong, Jian Kang, Hanghang Tong, and Jundong Li. 2021. Individual Fairness for Graph Neural Networks: A Ranking based Approach. In *Proceedings of the 27th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*.
- Part III: Beyond Group Fairness and Individual Fairness on Graphs
  - Rawlsian fairness
    - Aida Rahmattalabi, Shahin Jabbari, Himabindu Lakkaraju, Phebe Vayanos, Max Izenberg, Ryan Brown, Eric Rice, and Milind Tambe. 2021. Fair Influence Maximization: a Welfare Optimization Approach. In *Proceedings of the AAAI Conference on Artificial Intelligence*. 11630–11638.
  - Degree-related fairness
    - Xianfeng Tang, Huaxiu Yao, Yiwei Sun, Yiqi Wang, Jiliang Tang, Charu Aggarwal, Prasenjit Mitra, and Suhang Wang. 2020. Investigating and Mitigating Degree-Related Biases in Graph Convoltuional Networks. In *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*. 1435–1444.
  - Counterfactual fairness
    - Chirag Agarwal, Himabindu Lakkaraju, and Marinka Zitnik. 2021. Towards a Unified Framework for Fair and Stable Graph Representation Learning. *arXiv preprint arXiv:2102.13186* (2021)

7 RELATED TUTORIALS

The following list includes most relevant tutorials that will be or have been presented in other prominent data mining and machine learning conferences, as well as the similarities and differences compared with ours.

- **Fairness in Networks**
  - **Presenters**: Sorelle Friedler, Carlos Scheidegger, Suresh Venkatasubramanian, Aaron Clauset
  - **Conference**: KDD, Aug 14 - 18, 2021, Virtual Conference
  - **Connection**: Both tutorials aim to introduce recent advances in algorithmic fairness on graphs.
  - **Difference**: The related tutorial mainly focuses on algorithmic fairness in information access and influence maximization, whereas our tutorial present fairness on graphs in a much broader scope. Our tutorial differs the related tutorial in two aspects: (1) we review about a variety of fundamental fairness notions including group fairness, individual fairness, Rawlsian fairness, degree-related fairness and counterfactual fairness; (2) we present research works on a wide range of graph mining problems including not only influence maximization but also many other fundamental tasks like ranking, clustering, representation learning and classification.
- **Network Alignment: Recent Advances and Future Trends**
  - **Presenters**: Si Zhang, Hanghang Tong
  - **Conference**: CIKM, Oct 19 – 23, 2020, Virtual Conference
  - **Connection**: Both tutorials aim to present recent advances in graph mining.
  - **Difference**: Our tutorial focuses on algorithmic fairness on graphs, which is a totally different topic compared with the related tutorial on network alignment.
- **Fairness in Unsupervised Learning**
  - **Presenters**: Deepak S. Padmanabhan, Joemon M. Jose, Sanil Viswanathan Nair
  - **Conference**: CIKM, Oct 19 – 23, 2020, Virtual Conference
  - **Connection**: Both tutorials aim to introduce recent advances in algorithmic fairness.
  - **Difference**: The related tutorial presents studies on fairness of unsupervised learning in IID data, whereas our tutorial is specifically focused on algorithmic fairness on graphs and covers both supervised learning and unsupervised learning on non-IID graph data.
- **Representation Learning and Fairness**
  - **Presenters**: Moustapha Cisse, Sanmi Koyejo
  - **Conference**: NeurIPS, Dec 8 - 14, 2019, Vancouver, Canada
  - **Connection**: Both tutorials aim to introduce recent advances in algorithmic fairness.
  - **Difference**: The related tutorial focuses on the intersection of representation learning and algorithmic fairness in IID data, whereas our tutorial focuses on algorithmic fairness in non-IID graph data.
- **Defining and Designing Fair Algorithms**
  - **Presenters**: Sam Corbett-Davies, Sharad Goel
  - **Conference**: ICML, Jul 10 - 15, 2018, Stockholm, Sweden
  - **Connection**: Both tutorials aim to introduce recent advances in algorithmic fairness.

- **Difference**: The related tutorial reviews intrinsic limitations of existing fairness notions in machine learning and sheds light on designing fair algorithms with ideas from economics and legal theory, whereas our tutorial focuses on review state-of-the-art techniques about enforcing a wide range of fairness notions on graph mining algorithms.

- **Fairness in Machine Learning**
  - **Presenters**: Solon Barocas, Moritz Hardt
  - **Conference**: NeurIPS, Dec 4 - 9, 2017, Long Beach, CA, USA
  - **Connection**: Both tutorials aim to introduce recent advances in algorithmic fairness.
  - **Difference**: The related tutorial mainly focuses on group fairness and counterfactual fairness in traditional machine learning with IID data, whereas our tutorial focuses on algorithmic fairness on graphs, including group fairness, individual fairness and other fairness notions like Rawlsian fairness, counterfactual fairness.

ACKNOWLEDGEMENT

This work is supported by National Science Foundation under grant No. 1947135, and 2003924, by the NSF Program on Fairness in AI in collaboration with Amazon under award No. 1939725, by NIFA award 2020-67021-32799, and Army Research Office (W911NF2110088) The content of the information in this document does not necessarily reflect the position or the policy of the Government or Amazon, and no official endorsement should be inferred. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation here on.

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