Algorithmic Fairness on Graphs: State-of-the-Art and Open Challenges

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Abstract

Graph is a ubiquitous type of data that appears in many real-world applications, including social network analysis, recommendations and financial security. Important as it is, decades of research have developed plentiful computational models to mine graphs. Despite its prosperity, concerns with respect to the potential algorithmic discrimination have been grown recently. Algorithmic fairness on graphs, which aims to mitigate bias introduced or amplified during the graph mining process, is an attractive yet challenging research topic. The first challenge corresponds to the theoretical challenge, where the non-IID nature of graph data may not only invalidate the basic assumption behind many existing studies in fair machine learning, but also introduce new fairness definition(s) based on the inter-correlation between nodes rather than the existing fairness definition(s) in fair machine learning. The second challenge regarding its algorithmic aspect aims to understand how to balance the trade-off between model accuracy and fairness. This tutorial aims to (1) comprehensively review the state-of-the-art techniques to enforce algorithmic fairness on graphs and (2) enlighten the open challenges and future directions. We believe this tutorial could benefit researchers and practitioners from the areas of data mining, artificial intelligence and social science.

1 Target Audience

The tutorial is designed for researchers and practitioners in data mining, artificial intelligence, social science and other interdisciplinary areas. The prerequisites include basic knowledge on probability, linear algebra, data mining and machine learning. No prior knowledge on algorithmic fairness or any specific algorithm is required. This tutorial is designed for 40% novice, 30% intermediate, 30% expert, in order to achieve a good balance between the introductory and advanced materials. During the tutorial, we will alter between lecture and discussion with the audience to encourage audience participation. We will also post the materials of this tutorial (e.g., tutorial description, presentation slides, pre-recorded videos) for post-tutorial dissemination.

2 Tutorial Length

The length of the tutorials will 2 hours.

3 Presenter Biography

Jian Kang is currently a Ph.D. student in the Department of Computer Science at the University of Illinois at Urbana-Champaign. 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 trustworthy learning and mining on graphs. His research works on related topics have been published at several major conferences and journals in data mining. He has also served as a reviewer and a program committee member in top-tier data mining 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 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), and four best paper awards (TUP'14, CIKM'12, SDM'08, ICDM'06). He has published over 100 refereed articles. He is the Editor-in-Chief of SIGKDD Explorations (ACM), an action editor of Data Mining and Knowledge Discovery (Springer), and an associate editor of Knowledge and Information Systems (Springer); and has served as a program committee member in data mining, database and artificial

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intelligence venues (e.g., SIGKDD, SIGMOD, AAAI, WWW, CIKM). He is a Fellow of IEEE. For more information, please refere to his personal website at `http://tonghanghang.org/`.

4 Outline of Tutorial

- **Introduction**
  We will discuss with the background knowledge, then briefly review existing problem definitions, settings and the key challenges. Finally, We will also introduce problems in relation to algorithmic fairness on graphs, including auditing [7], explainability [5], robustness [18], privacy [17] and uncertainty quantification [8].
  - Background and motivations
  - Problem definitions and settings
  - Key challenges
  - Related problems
- **Part I: Group Fairness on Graphs**
  In this part, we will discuss how to enforce fairness among nodes of different demographic groups, i.e., group fairness, for classic graph mining (e.g., ranking, clustering) and for advanced graph mining (e.g., graph neural networks).
  - Classic graph mining [15, 14]
  - Advanced graph mining [2, 11, 3]
- **Part II: Individual Fairness on Graphs**
  In this part, we will introduce how to operationalize individual fairness on graphs (i.e., treating similar nodes with similar outcomes) from two different perspectives.
  - Optimization-based methods [6, 12]
  - Ranking-based methods [4]
- **Part III: Other Fairness Notions on Graphs**
  In this part, we will study how to enforce two fairness notions on graphs as follows, other than the extensively studied group fairness and individual fairness.
  - Degree-related fairness [13, 9]
  - Counterfactual fairness [1, 10]
- **Part IV: Beyond Fairness on Graphs**
  In this part, we will discuss problems in relation to fairness, as well as their corresponding state-of-the-art techniques.
  - Interpretability [5]
  - Adversarial Robustness [18]
  - Uncertainty quantification [8]
  - Accountability [7]
- **Part V: Future Trends**
  In this part, we elucidate open challenges and future directions from the following perspectives.
  - Benchmark datasets and evaluation metrics
  - Fairness on dynamic graphs
  - Fairness under uncertainty
  - Fairness vs. other social aspects

5 Related Tutorials

Here, we discuss the most relevant tutorials in other conferences, as well as the similarities/differences compared with ours.

- **Algorithmic Fairness on Graphs: Methods and Trends**
  - **Presenters**: Jian Kang, Hanghang Tong
  - **Conference**: KDD, Aug. 2021, Washington, D.C., USA
  - **Connection**: This is an earlier version of this tutorial on algorithmic fairness on graphs.
  - **Difference**: There will be some overlaps between the related tutorial and this tutorial (e.g., preliminaries and foundation of fair graph algorithms). However, in this tutorial, we will introduce recent advances that were not covered before (e.g., [5, 12, 8]) and provide new insights on the future directions (e.g., fairness under uncertainty).
- **Fair Graph Mining**
  - **Presenters**: Jian Kang, Hanghang Tong
  - **Conference**: CIKM, Nov. 2021, Virtual
  - **Connection**: This is an earlier version of this tutorial and the tutorial presented at KDD 2022 by the same presenters on algorithmic fairness on graph mining.
  - **Difference**: There will be some overlaps between the related tutorial and this tutorial (e.g., preliminaries and foundation of fair graph algorithms). However, in this tutorial, we will identify new challenge(s) (e.g., edge-level fairness), introduce recent advances that were not covered before (e.g., [14, 3, 9, 10, 5, 12, 8]) and provide new insights on the future directions (e.g., benchmark datasets and

evaluation metrics for algorithmic fairness on graphs, fairness under uncertainty, relationship between fairness and other social aspects such as interpretability, robustness, etc.)

- **Fairness in Networks**
  - **Presenters**: Sorelle Friedler, Carlos Scheidegger, Suresh Venkatasubramanian, Aaron Clauset
  - **Conference**: KDD, Aug. 2021, Virtual
  - **Connection**: Both tutorials aim to introduce fairness on graphs.
  - **Difference**: The related tutorial focuses on fairness from the social welfare perspective for 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 various fairness notions including group fairness, individual fairness, degree-related fairness and counterfactual fairness, in addition to the fairness from the social welfare aspect (e.g., the Rawlsian difference principle); (2) we include a wider coverage of research works in graph mining, including classic graph mining (e.g., ranking and clustering) and advanced graph mining (e.g., embedding and graph neural networks).

6 Potential Societal Impacts

This tutorial has several potential positive impacts to the society: (1) we hope this tutorial could attract research attention to promote fairness on graphs, which is less popular than fairness for IID data; (2) we hope this tutorial raises new challenges that are not addressed in the existing works; (3) we hope this tutorial could also benefit related research topic in identifying new problems and discovering its relationship to fairness on graphs.

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