

Causal Recommendation: Progresses and Future Directions

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ABSTRACT

Data-driven recommender systems have demonstrated great successes in various Web applications owing to the extraordinary ability of machine learning models to recognize patterns (*i.e.*, correlation) from the massive historical user behaviors. However, these models still suffer from several issues such as biases and unfairness due to spurious correlations. Considering the causal mechanism behind data can avoid the influences of spurious correlations brought by non-causal relations. In this light, embracing causal recommendation modeling is an exciting and promising direction. Therefore, causal recommendation is increasingly drawing attention in our recommendation community. Nevertheless, there lacks a systemic overview of this topic, leading to difficulties for researchers and practitioners to understand and keep up with this direction.

In this tutorial, we aim to introduce the key concepts in causality and provide a systemic review of existing work on causal recommendation. We will introduce existing methods from two different causal frameworks — the potential outcome framework and the structural causal model. We will give examples and discussions regarding how to utilize different causal tools under these two frameworks to model and solve problems in recommendation. A comparison between the two lines of work will be provided to facilitate understanding the differences and connections between them. Besides, we identify some open challenges and potential future directions for this area. We hope this tutorial could stimulate more ideas on this topic and facilitate the development of causality-aware recommender systems.

CCS CONCEPTS

• Information systems → Recommender systems.

KEYWORDS

Recommendation, Causality, Structural Causal Model, Neyman–Rubin Causal Model, Potential Outcome

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1 TOPIC AND RELEVANCE

1.1 Motivation

Recommender systems play an important role to help users alleviate information overload issues in the Web 2.0 era by providing personalized services for seeking information. To date, solving recommendation as a machine learning problem has become the default choice in practice. Learning-based recommender models, especially deep neural networks, have shown great advantages and huge improvements on a wide spectrum of real-world scenarios. Such data-driven models typically learn to forecast user-item interactions from historical records by recognizing the patterns correlated with interactions. However, such data-driven models largely suffer from bias issues (*e.g.*, popularity bias and selection bias) due to the uneven distribution of historical interactions [3], which can not only hurt recommendation accuracy but also causes unfairness [1], filter bubble [13], and echo chamber [5].

To tackle these issues, we embrace causal recommendation modeling, which dives into the cause-effect factors regarding user-item interactions. Generally, causal recommendation methods rank items by estimating the causal effect [14] on a user-item interaction instead of the conditional probability of the interaction¹. Different from the data-driven methods, causal recommendation considers the causal mechanisms behind data, such as the mechanism regarding the interaction generations process. In light of these mechanisms, we can leverage causal inference techniques to solve the aforementioned issues. For instance, we can recognize confounders [14] to eliminate spurious correlations, enhancing the accuracy and robustness of recommender models. Meanwhile, considering different types of causal effects and utilizing counterfactual inference can identify more reasonable fairness, removing the bad effects of sensitive features.

There are two main lines of research on causal recommendation regarding the underlying framework of causality utilized.

- *Potential Outcome*. In recent years, a surge of attention has been dedicated on the potential outcome framework [2, 16, 17], which are mainly based on two causal inference technologies — *inverse propensity scoring* (IPS) and *doubly robust* (DR). It is first used to unbiased learning-to-rank in explicit recommendation [17], then expanded to implicit recommendation [16]. Recently, based on joint learning or data fusion strategy, strands of new approaches are proposed, such as doubly robust joint learning [25], more robust doubly robust method [7], doubly robust targeted learning [32], multi-task (IPS/DR) learning [39], AutoDebias [2], and (IPS/DR)-LTD method [26].
- *Structural Causal Model*. The second line focuses on the structural causal model, which emerged in the last one to two years. Following the ladder of causation with three layers

¹Note that conventional recommender models estimate $P(y = 1|u, i)$ or $E(Y|u, i)$.

of association, intervention and counterfactual [14], these methods [4, 22, 23, 29, 41, 42] model recommendation at the intervention and counterfactual layers above the correlation in observed data. These methods resort to causal graph for analyzing the causal mechanisms of interaction generation and perform interventions or counterfactual inference over the observed data.

In this tutorial, we would like to introduce the current progress on both lines, discuss connections and differences between them, and identify open challenges and future directions.

Necessity and timely of this tutorial. Causal recommendation is new, but developing vigorously. In year 2021, there are more than 20 relevant publications in the top-tier conferences (e.g., *SIGIR* and *SIGKDD*) related to causal recommendation. Moreover, one of them [41] is awarded the SIGIR 2021 Best Paper Honorable Mention award². It is undoubted that these pioneer works will inspire more ideas, and their success will encourage more efforts in this topic, for designing more accurate, responsible, stable, and explainable recommender systems. Given the importance and initial but flourishing development of causal recommendation, we believe it is the right time to conduct a tutorial of this topic, so as to benefit the researchers and practitioners to understand current progress and further works on this topic. Besides, the Nobel Prize in Economic Sciences 2021 is also awarded for methodological contributions to the analysis of causal relationships³, which will largely stimulate relevant research topics, including causal recommendation.

To our knowledge, this is the first tutorial on this new but flourishing topic. Especially we find existing work are in two lines, which lie in different causal frameworks or philosophies. Our systemic reviews on these two lines of works will help beginners to fast step into these two directions, and keep up with the latest progress. Our comparison between two lines of works could help practitioners to understand the relations and differences between them and then choose suitable direction for themselves. Note that this area is far away mature and has many open problems. We also would like to arise discussions on these problems and propose some new directions, with the ambition of inspiring more new ideas and facilitating the development of this area.

1.2 Relevance

The topic of this tutorial is highly related to the World Wide Web, especially to recommender systems, user modeling, log analysis and Web mining in the Web systems. And the topic is becoming an important and flourishing direction in recommendation and may bring inspiration for other related Web applications. Before our tutorial, a workshop [40] on a similar topic was organized in SIGIR 2021 and received much attention. As to the WWW community with overlapped interested with IR community, we believe our tutorial will also attract great attention from the WWW community.

1.3 Outline

This tutorial focuses on causal recommendation. Here we present an outline of the topics to be covered with timing:

- Introduction. (15 Min, Xiangnan He)

²<https://sigir.org/sigir2021/awards/>.

³<https://www.nobelprize.org/prizes/economic-sciences/2021/press-release/>.

- Organization of the tutorial.
- Data-driven recommender system.
- The motivations for causal recommendation.
- The classification of causal recommendation methods: potential outcome framework [9] based methods and structural causal model [14] based methods.
- Potential outcome framework for recommendation. (60 Min, Peng Wu)
 - Key elements in potential outcome framework [31].
 - Basic methods, including inverse propensity score (IPS) [17], self-normalized inverse propensity score (SNIPS) [17, 19], error imputation based (EIB) [8, 18] learning, and doubly robust (DR) learning [6, 25].
 - Limitations of Basic Methods [32]. Evaluating the basic methods from five different aspects: doubly robust, robust to small propensities [30], boundedness [12, 21, 33], without extrapolation [12], and low variance.
 - Enhanced DR Methods, including more robust doubly robust (MRDR) [7], doubly robust targeted learning [32], and multi-task learning [39].
 - Uniform data-aware methods [2, 26, 37].
 - Causal analysis framework [31], providing formal causal definitions of various biases in recommender system.
- Q&A. (5 Min)
- Break. (10 Min)
- Structural causal model for recommendation (60 Min, Wenjie Wang and Yang Zhang)
 - A brief introduction to the structural causal model.
 - Dealing with confounding structures in recommendation.
 - * Confounders in recommendation.
 - * Strategies for dealing with observed confounders, focusing on backdoor adjustment based methods [22, 41].
 - * Strategies for unobserved confounders, including front-door adjustment [14] and learning substitutes [27, 43].
 - Considering colliding structures in recommendation.
 - * Colliders in recommendation and their influences.
 - * Modeling colliding effect, including generating special causal data [42] and optimizing the retraining of recommender system [4].
 - Counterfactual in recommendation.
 - * Counterfactual inference for recommendation, focusing on removing path-specific effects to deal with bias problems [23, 29].
 - * Counterfactual synthesizing in recommendation [28, 36, 38].
 - * Counterfactual fairness in recommendation [11].
 - * Counterfactual explanation for recommendation [20].
- Comparison between potential outcome framework based recommendation and structural causal model based recommendation. (5 Min, Fuli Feng)
 - The connections and differences between them.
- Open problems, future directions and conclusions. (20 Min, Fuli Feng)
 - Causality-aware evaluation methods.
 - Causal discovery in recommendation.
 - Path-specific counterfactual fairness.

- Causal graph for environments with many variables and variables that are difficult to define.
- Causal graph and causal methods for recommendation with a feedback loop.
- More automatic causal recommendation.
- Conclusions.
- **Q&A. (5 Min)**

1.4 Qualification of presenters

We have been working on recommendation and causal recommendation for a long time with a series of publications on causal recommendation [2, 22, 23, 29, 41, 42] emerged in several top-tier conferences, such as WWW 2021, SIGIR 2021, and SIGKDD 2021. These researches connect recommendation with structural causal models [22, 23, 29, 41], extend the potential outcome framework in recommender systems [2], and also develop some theoretical causal inference methods [30, 33, 34]. Notably, our work [41] received the SIGIR 2021 Best Paper Honorable Mention award. We are familiar with the two technical lines of this topic and have a systemic review of this topic. We thus believe our tutorial would be systemic and insightful. Moreover, our team has rich experience and has conducted more than 10 tutorials on various conferences including SIGIR, WWW, WSDM, CIKM and RecSys [3, 10, 15, 24, 35]. Specifically, our tutorials on SIGIR 2018 and CIKM 2019 attracted the largest number of audiences among the tutorials at the corresponding conferences.

2 TUTORIAL DETAILS

- **Duration.** The tutorial is planned as a 3 hours tutorial.
- **Interaction style.** This is a lecture-style tutorial. There is no need for the audience members to use any software during the tutorial.
- **Intended audience and level.** This tutorial is intended for the following researchers and practitioners in recommender system and other web areas:
 - who are new to the causal recommendation and look for a tutorial to fast step into this area.
 - who have knowledge of recommender systems and the knowledge of causality but do not know how to combine them or do not know what to do in the near future.
 - who are in other web areas but want to know how to utilize causal inference in real tasks like recommendation task.
 Only elementary knowledge on recommendation and basic probability and statistics is required. Attendees are expected to gain a global scope of this area, high-level understanding of different types of causality-aware recommendation methods, the latest progress, and some promising future directions.
- **Previous editions.** This is the first edition of this tutorial.
- **Tutorial materials.** The slides will be provided to attendees. Organizers can obtain copyright permission.
- **Video teaser.** We have released the teaser through Dropbox⁴.

⁴<https://www.dropbox.com/sh/v0slzvn40f88ee/AABDIaTcXxj---33UV5IIA51a?dl=0>.

- **Organization details.** The tutorial can be conducted online with the online meeting software. We will also provide a pre-recorded lecture if necessary. If allowed, we can also live the tutorial through popular video streaming platforms.

3 BIOS OF PRESENTERS

Yang Zhang⁵ is a Ph.D. student in the School of Information Science and Technology, University of Science and Technology of China (USTC), supervised by Prof. Xiangnan He. He received his B.E. degree from the USTC. His research interest lies in the recommender system and causal inference. He has two publications in the top conference SIGIR. His work on the causal recommendation has received the Best Paper Honorable Mention in SIGIR 2021. He has served as an invited reviewer for the journal TOIS.

Wenjie Wang⁶ is a Ph.D. student in the School of Computing, National University of Singapore. He received the B.E. degree from the School of Computer Science and Technology, Shandong University in 2019. His research interests cover causal recommendation, data mining, and multimedia. He has over 10 publications appeared in several top conferences such as SIGIR, KDD, ACMMM, and WSDM. Moreover, he has been served as the PC member and reviewer for the top conferences and journals including TKDE, TOIS, SIGIR, AAAI, MM, WSDM, ECML/PKDD.

Dr. Peng Wu is a postdoctoral student in Beijing International Center for Mathematical Research, Peking University. His research interests include causal inference, recommender systems, and policy learning. He has over 10 publications appeared in several journals such as IEEE Transactions on Geoscience and Remote Sensing, Journal of Statistical Planning and Inference, Canadian Journal of Statistics, Mathematical Biosciences and Engineering, and Computational Statistics.

Dr. Fuli Feng⁷ is a Research Fellow in the School of Computing, National University of Singapore (NUS). He received Ph.D. in Computer Science from NUS in 2019. His research interests include information retrieval, data mining, and multi-media processing. He has over 30 publications appeared in several top conferences such as SIGIR, WWW, and KDD, and journals including TKDE and TOIS. His work on the causal recommendation has received the Best Paper Honorable Mention in SIGIR 2021. His work on Bayesian Personalized Ranking has received the Best Poster Award of WWW 2018. Moreover, he has been served as the PC member for several top conferences including SIGIR, WWW, WSDM, NeurIPS, AAAI, ACL, MM, and invited reviewer for prestigious journals such as TOIS, TKDE, TNNLS, TPAMI, and TMM.

Dr. Xiangnan He⁸ is a professor with the University of Science and Technology of China (USTC). His research interests span information retrieval, data mining, and applied machine learning. He has over 100 publications appeared in top conferences such as SIGIR, WWW, and KDD, and journals including TKDE, TOIS, and TNNLS. His work on recommender system has received the Best Paper Award Honourable Mention in SIGIR (2021, 2016) and WWW (2018). He has rich teaching experience, including presenting the tutorial “Bias Issues and Solutions in Recommender System” in

⁵<https://scholar.google.com/citations?user=M9NcazMMAAAJ>.

⁶<https://scholar.google.com/citations?user=Ma5DtmoAAAAJ&hl=en>.

⁷<https://scholar.google.com.sg/citations?user=QePM4u8AAAAJ&hl=en>.

⁸<https://scholar.google.com.sg/citations?user=X45Go24AAAAJ>.

WWW 2021 and Recsys 2021, and the tutorial "Learning and Reasoning on Graph for Recommendation" in WSDM 2020 and CIKM 2019, and the tutorial "Deep Learning for Matching in Search and Recommendation" in WSDM 2019 and SIGIR 2018.

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