Towards Secure and Robust Recommender Systems: A Data-Centric Perspective

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ABSTRACT

As recommender systems (RS) continue to evolve, the field has seen a pivotal shift from model-centric to data-centric paradigms, where the quality, integrity, and security of data are increasingly becoming the key drivers of system performance and personalization. This transformation has unlocked new avenues for more precise and tailored recommendations, yet it also introduces significant challenges. As reliance on data intensifies, RS face mounting threats that can compromise both their effectiveness and user trust. These challenges include (1) Malicious Data Manipulation, where adversaries corrupt or tamper with datasets, distorting recommendation outcomes and undermining system reliability; (2) Data Privacy Leakage, where adversarial actors exploit system outputs to infer sensitive user information, leading to serious privacy concerns; and (3) Erroneous Data Noise, where inaccuracies, inconsistencies, and redundant data obscure the true user preferences, degrading recommendation quality and user satisfaction. By focusing on these critical data-centric challenges, this tutorial aims to equip participants with the knowledge to build RS that are secure, privacy-preserving, and resilient to data-driven threats, ensuring reliable and trustworthy performance in real-world environments. In addition, attendees will gain hands-on experience with our newly released toolkit for RS-based attacks and defenses, providing them with practical, actionable insights into safeguarding RS against emerging vulnerabilities.

COVER SHEET

Tutorial Length. The tutorial lasts for 3 hours, plus a 20-min break.

Intended Audience. This tutorial is suitable for attendees with intermediate knowledge of RS, but also accessible to those with basic familiarity in machine learning or data mining. No advanced expertise is required.

Relevant Tutorials. There is only one relevant prior tutorial on trustworthy RS[1], which broadens its scope to provide an introduction and future outlook on the entire landscape of trustworthy RS. However, its coverage of security and robustness remains relatively superficial. In contrast, our tutorial focuses specifically on secure and robust RS, offering an in-depth analysis from a data-centric view. This approach allows for a more comprehensive and profound understanding of the field.

Brief Biography of Presenters:

- **Prof. Hongzhi Yin** is an ARC Future Fellow, Full Professor, and the Director of the Responsible Big Data Intelligence Lab at The University of Queensland. He has published 300+ papers with an H-index of 77, making notable contributions to RS, graph learning, decentralized learning, and edge intelligence. He has rich lecture experience and taught five relevant courses, such as information retrieval and web search, social media analytics, and responsible data science. Additionally, he has delivered 20+ keynotes and tutorials at the top-tier conferences like WWW'17,22,24, DASFAA'23, and KDD'17.
- **Mr. Zongwei Wang** is currently pursuing his Ph.D. at Chongqing University and is a visiting student at The University of Queensland. His research work has been published on top data mining conferences such as KDD, TIST, PAKDD, WSDM, etc. He has ample experience tutoring relevant courses and has presented his work at multiple top-tier conferences, such as KDD and PAKDD.
- **Dr. Junliang Yu** is an ARC DECRA Fellow at the University of Queensland. His research interests include RS, data-centric AI, and graph learning. With over 30 publications in premier venues, he is a recognized contributor in his field. He has delivered multiple lectures at summer schools and taught courses on RS and social media analytics. He organized two well-received tutorials on self-supervised RS at WWW'22 and DASFAA'23, and presented his work at multiple top-tier conferences.
- **Dr. Tong Chen** is a Senior Lecturer and ARC DECRA Fellow at The University of Queensland. His research on lightweight, on-device, and trustworthy RS has been published on top-tier international venues such as KDD, SIGIR, WWW, TKDE, WSDM, TNNLS, TOIS, and CIKM. He has ample track records in lecturing, witnessed by his course design and delivery experience in business analytics, teaching experience in data science, as well as invited tutorials on cutting-edge RS at the WWW'22,24, and DASFAA'23.
- **Prof. Shazia Sadiq** is a Full Professor at The University of Queensland. Her research focuses on responsible data management and aims to reduce the socio-technical barriers to data driven transformation. She is the Fellow of the Australian Academy of Technological Sciences and Engineering. Throughout her 25 year career, she has received numerous invitations to speak at prestigious conferences, academic institutions, and industry forums, delivering over 20 tutorials, talks, panels and keynotes. One notable example is the Keynote talk at SIGMOD'23.
- **Prof. Min Gao** works as a Full Professor at Chongqing University, China. She has published 100+ papers, making notable contributions to RS and data mining. She has been SPC or PC for many top conferences, such as WWW, IJCAI, AAAI, KDD, WSDM, and CIKM. Prof. Min Gao has rich lecture experience and taught three relevant courses, such as advanced machine learning, computer networks, and advanced database, and has presented her work at multiple top-tier conferences.

* Min Gao is the contact person.
[1] https://advanced-recommender-systems.github.io/trustworthiness-tutorial/

1 MOTIVATION AND TARGET AUDIENCE

Advanced recommender systems (RS) have become essential tools for mitigating the problem of information overload in a wide array of real-world applications. Over the past few decades, recommendation models have undergone substantial evolution, moving from traditional collaborative filtering techniques [12, 20, 49] to more sophisticated approaches grounded in deep learning [2, 7, 8, 24, 35]. However, as these models continue to expand in both size and complexity, the primary bottleneck impeding further improvements in recommendation performance is increasingly shifting from model architecture to the quality of the underlying recommendation data. In response, rather than exclusively concentrating on the development of more advanced models, an emerging trend among researchers is to focus on enhancing data quality. This has led to a significant shift toward data-centric methodologies in the field. Such a transition represents a pivotal advancement in the ongoing evolution of RS, ushering in a new era of data-centric RS, where the refinement of data quality is prioritized as a key driver of system performance [13].

The fundamental premise of data-centric RS is that the quality of the data ultimately determines the upper limits of a model's performance. High-quality recommendation data allows RS to more accurately capture user preferences, resulting in recommendations that are better aligned with users' expectations and need [9, 42, 50]. While improving data quality is essential for enhancing the effectiveness of recommendations, ensuring the security and robustness of that data is equally critical for maintaining the reliability and trustworthiness of RS [6, 21, 23, 39, 48, 54]. Vulnerabilities in data, such as malicious manipulation, privacy breaches, or the introduction of noisy or inaccurate data, can severely compromise system performance, leading to unreliable or biased recommendations. Moreover, in real-world applications where users increasingly rely on RS for decision-making, even minor data issues can erode trust in the system. In this context, the shift to data-centric RS not only emphasizes the refinement of data quality but also highlights the importance of safeguarding the data from security threats and ensuring its robustness against adversarial attacks. As researchers and practitioners continue to prioritize data-centric approaches, the focus on both data quality and security becomes paramount, shaping the future landscape of RS research and applications.

This tutorial is designed for a broad audience, including academic and industrial researchers, graduate students, and practitioners from the recommendation field and related areas. By the end of the tutorial, participants will have a solid understanding of basic poisoning attacks and defensive strategies to enhance the robustness and security of recommendation systems. Additionally, they will gain hands-on experience using an open-source toolkit. While prior knowledge of recommendation systems is preferred, the tutorial will also cover foundational concepts to ensure better engagement and accessibility for all attendees.

2 OUTLINE OF THE TOPICS TO BE COVERED

This tutorial seeks to provide a comprehensive introduction to secure and robust recommendations by focusing on three key aspects from a data-centric perspective, while also outlining future directions for advancing this field.

(1) Securing Data Integrity - Defending Against Malicious Manipulation in RS. In data-centric RS, the integrity of recommendation data is crucial for ensuring reliable performance and trustworthy outcomes. Attackers, however, can target this data by corrupting training datasets or manipulating model gradients, ultimately distorting recommendation results and undermining system performance [16, 22, 34]. These attacks exploit weaknesses in the data pipeline, from data collection to model training, introducing biases that lead to inaccurate or skewed recommendations. From a data-centric perspective, protecting the integrity of recommendation data is essential. Attackers strategically select data points to corrupt or manipulate gradients, which highlights the importance of understanding how these malicious interventions can influence the system's decision-making process [3, 14]. By identifying and analyzing these vulnerabilities, more robust strategies can be developed to safeguard data integrity. Furthermore, defensive measures such as data validation, anomaly detection, and adversarial training are being employed to enhance the resilience of RS against data-centric attacks, ensuring system reliability and robustness in the face of adversarial manipulation [1, 10, 32].

In this tutorial, a comprehensive framework will be presented that encompasses both the understanding of potential vulnerabilities and the development of strategies to protect the integrity of recommendation data. The framework will explore the various methods attackers use to corrupt or manipulate data, along with the defensive techniques employed to counter these threats.

(2) Preserving Data Privacy – Defending Against Adversarial Inference in RS: In data-centric RS, protecting user privacy is critical, yet increasingly challenging as adversarial inference attacks become more sophisticated [5, 37, 40, 45]. These attacks exploit the rich data generated by RS to uncover sensitive information. For example, membership inference attacks allow adversaries to determine whether a particular user's data was included in the training set, while attribute inference attacks enable the extraction of private user attributes that were meant to remain undisclosed [15, 33, 38, 44]. Such breaches compromise user trust and present significant ethical and legal challenges in deploying RS across industries.

This tutorial will provide an in-depth exploration of these privacy attacks, focusing on how adversaries exploit vulnerabilities in the data pipeline of RS to compromise user privacy. By examining membership and attribute inference attacks, participants will gain a deeper understanding of how sensitive data can be extracted from RS outputs. To counter these threats, a range of defense mechanisms will be discussed, including data obfuscation, limiting information leakage, and the integration of privacy-preserving techniques during both training and inference phases. These strategies are designed to uphold user privacy while maintaining the effectiveness of data-centric RS.

(3) Managing Data Noise – Overcoming the Impact of Inaccurate and Redundant Data in RS: In data-centric RS, the quality of data directly influences the accuracy of predictions and overall user satisfaction. Data noise—arising from inaccurate, redundant, or irrelevant information—can significantly degrade system performance by introducing inconsistencies that obscure true user preferences [11, 51, 52]. This noise can come from a variety of sources, including

repeated interactions, cross-platform preference inconsistencies, or even intentionally injected malicious data [4, 19, 30, 31, 43]. Addressing data noise is essential for maintaining the reliability of RS in data-centric environments, where system success hinges on data quality.

This tutorial will provide a systematic investigation into the origins of noisy data in RS and introduce corresponding solutions to filter and mitigate its effects. Solutions will be explored across multiple approaches aimed at identifying, filtering, and minimizing the impact of noisy data on RS. These include techniques for selecting high-quality data, adjusting training processes to be more resilient to noise, and refining datasets to focus on the most relevant and informative data. By concentrating on these data-centric methods, this session will provide participants with practical strategies to improve the accuracy, reliability, and overall robustness of RS, even in the presence of noisy or inconsistent data.

(4) Research Limitations and Future Opportunities: Despite recent progress, current data-centric research on secure and robust RS still faces several limitations, presenting ample opportunities for further investigation. In this tutorial, we will highlight the gaps in existing studies and propose innovative directions to advance the field of secure and robust RS. Moreover, we will explore how the integration of large language models (LLMs) can introduce new dimensions to these systems, offering a promising avenue for enhancing both their security and robustness. By identifying these key areas for future research, we aim to pave the way for the continued development of more secure and robust RS.

3 RELEVANCE TO THE COMMUNITY AND REFERENCES TO RELATED RESOURCES

Our team is recognized as a pioneer in the field of robust and secure recommender systems, consistently contributing to both academic and practical advancements in this domain. Over the years, our work on secure and reliable recommendation systems, in collaboration with co-authors, has been published in top-tier venues such as KDD, WWW, SIGIR, TKDE, WSDM, and TOIS, significantly influencing the research community. Beyond academic publications, we actively contribute to the broader RS community by developing open-source frameworks[2][3][4] for benchmarking recommender systems, which have collectively garnered over 2,000 stars on GitHub. These contributions reflect our dedication to supporting the growth and adoption of secure, privacy-preserving, and resilient recommender systems within the community.

- Securing data integrity: [17, 25, 28, 29, 36, 41, 46, 53].
- Preserving Data Privacy: [5, 37, 38, 40, 45, 48].
- Managing Data Noise [26, 47].
- Two survey papers on secure recommendation [18, 27].
- ARLib - A toolkit for secure and robust recommendation.

4 FORMAT AND DETAILED SCHEDULE

The tutorial is delivered as a lecture-style tutorial with extra hands-on experience (3 hours in duration plus a 20-min break). The schedule and detailed organization of the topics are as follows.

I. Introduction (20 mins)

(1) Overview of Recommender Systems (5 mins)
(2) Introduction of Data-Centric Recommender Systems and its confronted Issues (15 mins)

II. Securing Data Integrity - Defending Against Malicious Manipulation in Recommender Systems (40 mins)

(1) Motives and Types of Malicious Manipulation Attacks (20 mins)
(2) Defense Against Malicious Manipulation Attacks (20 mins)

III. Preserving Data Privacy – Defending Against Adversarial Inference in Recommender Systems (40 mins)

(1) Types of Inference Attacks against Data Privacy (20 mins)
(2) Data Privacy-Preserving Methods (20 mins)

IV. Managing Data Noise – Overcoming the Impact of Inaccurate and Redundant Data in Recommender Systems (40 mins)

(1) Origins and Types of Data Noises (20 mins)
(2) Data Denoising Methods (20 mins)

V. Research Limitations and Future Opportunities (20 mins)

(1) Extension of Existing Research Questions (10 mins)
(2) Security of Large Language Models-Driven Recommender Systems (10 mins)

VI. Open-source Toolkit for Robust and Secure Recommendation (20 mins)

5 TYPE OF SUPPORT MATERIALS TO BE SUPPLIED TO ATTENDEES.

The tutorial materials, including the slides and video recordings, will be made available online in advance for attendees via the tutorial homepage[5] on GitHub. To avoid the potential occurrence of technical problems, a pre-recorded lecture will be uploaded to YouTube beforehand.

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