Towards a Responsible Web: Economic Perspectives on Fairness in Information Retrieval

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Abstract

Fairness is a crucial aspect of a responsible web, as algorithms may discriminate against certain groups and harm the overall web ecosystem. To address this issue, numerous fairness-aware information retrieval (IR) models and evaluation metrics have been proposed. However, the inherent complexity of both fairness and IR systems makes it difficult to systematically summarize the progress achieved so far. This complexity calls for a more structured and novel perspective to re-examine and guide future directions in fairness-aware IR research.

The field of economics has a long history of studying fairness, providing a rich theoretical and empirical foundation. The web ecosystem can be viewed as a specialized economic market, where a system-oriented perspective enables the integration of IR fairness into a broader and more structured framework.

In this tutorial, we begin by drawing parallels between the components of IR systems and those of economic markets, illustrating how IR systems can be understood as a form of economic system. Next, we organize fairness algorithms within an economic cube, where each dimension represents a distinct fairness taxonomy: macro vs. micro, demand vs. supply, and short-term vs. long-term. Finally, we demonstrate how this economic framework can be applied to most fairness algorithms and a variety of real-world IR applications. Unlike previous fairness-aware tutorials, our tutorial not only offers a clear and novel perspective on fairness but also encourages the use of economic tools to address fairness challenges. We hope it provides a fresh and comprehensive outlook on building a responsible web, while highlighting open problems and promising directions for future research.

CCS Concepts

• **Information systems → Information retrieval**.

Keywords

Information retrieval, Fairness, Economics

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1 Topic and Relevance

1.1 Background: Fairness in IR

Information retrieval (IR) systems form a fundamental part of the modern web, serving as key infrastructures that help users efficiently access information [47]. However, beyond merely retrieving information, IR systems (*e.g.,* search engines) actively influence a user's behavior and decisions through the information they present [35]. Therefore, it is essential for IR systems to consider broader beyond-accuracy objectives such as fairness [22] and bias mitigation [7], which are vital for sustaining a healthy and responsible web ecosystem [7, 22]. Among these objectives, fairness plays a particularly critical role: it ensures that IR systems do not discriminate against specific user groups [33, 36, 41] and that they provide equitable support to the long tail of valuable creators [28, 29, 39].

Although a wide range of fairness-aware IR algorithms have been proposed, they are fragmented across more than ten distinct dimensions [3, 12, 20, 37]. This fragmentation reflects the multifaceted nature of fairness itself and the complex, multi-stakeholder structure of web-based IR systems [1], where users, items, creators, and platforms each pursue distinct objectives. Such complexity poses significant challenges for developing a unified understanding of fairness within IR and for charting clear research directions.

In the broader vision of a responsible web, addressing this challenge is crucial. Without a systematic framework that connects these diverse notions of fairness, IR systems risk reinforcing inequalities or misaligning with societal values. A more coherent perspective is therefore needed to integrate fairness into the design of web ecosystems that are transparent, inclusive, and sustainable.

1.2 An Economic Perspective on Fairness in IR

Drawing inspiration from the rich body of literature in economics, we propose to use established economic theories to systematically interpret and address the complex fairness challenges. In this tutorial, we first illustrate how IR systems can be conceptualized as specialized economic markets, where users act as consumers, items or documents serve as suppliers, and the platform functions as a central regulator balancing ecosystem stability with short- and long-term utility, analogous to the role of the government or market regulators [44]. In this market analogy, users seek high-quality information or products, providers compete for visibility and exposure, and the platform strives to balance profit maximization with user satisfaction by delivering personalized services.

Moreover, the IR environment, like an economic market, operates under resource constraints, for example, limited ranking positions, and ranking scores can be viewed as analogues to market prices that determine exposure and attention [6]. Given these structural parallels, it becomes natural and promising to draw connections between fairness concepts in economics and fairness objectives in IR, paving the way toward a more principled and systematic foundation for a responsible web.

Benefits of using an economic perspective. The field of economics has a long tradition of studying fairness, with a central focus on how to allocate limited resources to best satisfy people's unlimited needs and desires [17, 30]. Grounded in a mature theoretical and empirical foundation, an economic perspective provides a powerful lens through which to analyze fairness, offering a more systematic and principled framework for addressing the complex challenges of fairness in IR.

Moreover, economics inherently examines the interactions among multiple stakeholders and evaluates their outcomes across different time horizons. This systems-oriented perspective aligns closely with the structure of modern IR ecosystems, where users, providers, and platforms continually interact over both short- and long-term objectives. By embedding IR fairness within this broader context of societal and intertemporal trade-offs, researchers can move beyond ad hoc formulations toward a more coherent understanding of fairness.

1.3 Necessity and Timeliness of this Tutorial

Given the growing urgency of building fair and trustworthy IR systems, now is the right time to offer a tutorial that helps researchers and practitioners summarize current progress and explore future responsible web directions. Our tutorial introduces a fresh and well-structured economic perspective on emerging fairness challenges in IR. This perspective not only deepens participants' understanding of fairness issues within complex web ecosystems but also equips them with economic reasoning and analytical tools to design more equitable, transparent, and sustainable IR systems.

1.4 Relevance

This tutorial is highly relevant to the core themes of TheWebConf, with a specific focus on fairness, accountability, transparency, ethics, and explainability (FATE), poised to inspire advancements in other trustworthy associated web applications.

Regarding fairness in information retrieva;, several related tutorials been offered: (i) **Recsys'19, SIGIR'19** [10], which considers fairness mainly from user study and evaluation perspective; (ii) **Recsys'20** [13], which proposes different tools and strategies to mitigate and evaluate unfairness in IR; (iii) **SIGIR'21** [23], which proposes a taxonomy on fairness-aware algorithms in recommender systems; and (iv) **CIKM'22** [11], which focuses on a fairness taxonomy for search systems from the machine learning perspective.

The key distinction of our tutorial is that we organize the body of knowledge on fairness in IR through the structured lens of economics. This unique perspective not only provides a systematic way to understand fairness in IR but also introduces economic tools that guide the design of fair IR algorithms.

1.5 Qualification of Tutors

We have been working on fairness problems in information retrieval for a long time, underscored by a series of publications on the top-tier conferences and journals [24, 25, 31–33, 39, 42–44]. Our team also has a strong educational background and working experience in an economic-related field. A highlight of our contributions includes two papers on IR fairness [39, 44], which were honored with the Spotlight-Best Paper Candidates at TheWebConf 2023 and the Best Paper Honorable Mention for SIGIR 2024. Moreover, our team has rich tutorial experience and has presented dozens of tutorials at various top-tier conferences, including SIGIR, TheWebConf, WSDM, KDD and RecSys [8, 18, 26]. Our team also implemented a fairness-aware algorithm toolkit [40]. Thus, we believe we are well-equipped and that our tutorial will be comprehensive and insightful.

2 Tutorial Type

This tutorial will be a half-day lecture-style tutorial.

3 Format and Schedule

The outline for this tutorial is as follows:

00:00–00:20 Introduction (Maarten)
- Organization of the tutorial.
- Introduction of IR systems.
- Introduction of fairness in IR.

00:20–00:50 An Economic View on Fairness in IR (Chen)
- Relating IR systems to the economic markets.
- Re-framing fairness in IR through economics.

00:50–01:00 Q&A

01:00–01:30 Economics-based Fairness Mitigation and Evaluation Strategies I (Chen)
- Objective: demand vs. supply
  - Demand (user) fairness [19, 21, 33, 38].
  - Supply (provider) fairness [4, 9, 39, 43, 44].
  - Economic tools: taxation [44].

Break, with Q&A

01:30–02:00 Economics-based Fairness Mitigation and Evaluation Strategies II (Clara)
- Scale: macro vs. micro
  - Micro (individual) fairness [34].
  - Macro (group or amortized) fairness [5, 28, 39, 43].
  - Economic tools: game theory [2].

02:00–02:30 Economics-based Fairness Mitigation and Evaluation Strategies III (Yuanna)
- Time: long-term vs. short-term
  - Long-term or dynamic fairness [14, 27, 45].
  - Short-term or static fairness [29, 39, 44].
  - Economic tools: risk theory [15].

02:30–02:50 Future Directions, and Conclusions (Maarten)

- Future direction in the IR markets.
- Insights from an economic perspective.
- Fairness toolkit
- Conclusions.

02:50–03:00 Q&A

4 Intended Audience

This tutorial examines fairness in IR from an economic perspective, making it valuable for researchers, practitioners, and students interested in fairness, bias, and trustworthiness in Web systems such as search and recommendation, as well as those exploring economic aspects of the web. It requires only a basic understanding of IR and fairness, with no prior background in economics. The tutorial introduces essential economic concepts, such as taxation and interest rates, through clear, intuitive examples to ensure accessibility and understanding. We aim for the audience to learn how to apply economic frameworks and tools to understand fairness issues, and to extend this perspective to broader challenges such as bias and misinformation.

5 Brief Biographies

Chen Xu is a final-year Ph.D. student at the Gaoling School of Artificial Intelligence, Renmin University of China. His current research interests lie in fairness problems in IR from an economic perspective. He earned a double bachelor's degree in computer science and economics. He has published over ten papers in top-tier conferences and journals such as SIGIR, TheWebConf, CIKM, TOIS. Chen Xu is the first author of the Spotlight-Best Paper Candidates for TheWebConf 2023 and the Best Paper Honorable Mention for SIGIR 2024 with fairness issues in IR. He has delivered tutorials at KDD and WSDM, focusing on innovative topics in fairness.

Clara Rus is a third-year Ph.D. student at IRLab, University of Amsterdam. Her research focuses on fairness in IR, particularly intersectional fairness-aware learning to rank for algorithmic hiring. She has publications on the topic of fairness-aware rankings in venues such as RecSys, CIKM, and ECIR. Additionally, she delivered lectures on fairness-aware rankings as part of the Fairness and Intersectional Non-Discrimination in Human Recommendation (FINDHR) European project.

Yuanna Liu is a fourth-year Ph.D. student at IRLab, University of Amsterdam. Her research focuses on fairness in IR. She has published papers on the topic of fairness-aware next basket recommendation at conferences such as SIGIR and RecSys. Additionally, she delivered lectures on the evaluation of recommender systems as a teaching assistant for courses on recommender systems.

Marleen de Jonge is a Ph.D. student. Her current research interests focus on the application of both deep learning and econometric methods for macro-financial research. She holds a bachelor's degree in artificial intelligence and a master's degree in econometrics. Formerly, she published work on evolutionary computation and climate finance and worked in the Financial Stability division of the Dutch central bank, De Nederlandsche Bank (DNB).

Jun Xu is a Professor at the Gaoling School of Artificial Intelligence, Renmin University of China. His research interests focus on applying machine learning to IR. He has published about 100 papers and 2 monographs at top international journals and conferences. He has served or is serving top international conferences as Senior PC members at SIGIR, TheWebConf, CIKM, and top international journal of JASIST as an editorial board member, and ACM TIST as an associate editor. He has given tutorials at top conferences like SIGIR, WSDM, TheWebConf and KDD on the topic of deep learning and fairness in IR.

Maarten de Rijke is a Distinguished University Professor of Artificial Intelligence and Information Retrieval at the University of Amsterdam. His research focuses on developing and evaluating trustworthy technologies that connect people with information, including search engines, recommender systems, and conversational assistants. He serves as the scientific director of the Innovation Center for Artificial Intelligence and has held key editorial roles, including former Editor-in-Chief of ACM Transactions on Information Systems and Foundations and Trends in Information Retrieval. He is currently a Co-Editor-in-Chief of Springer's Information Retrieval book series and an (associate) editor for various journals and book series. Additionally, he has served as General (Co-)Chair or Program (Co-)Chair for conferences such as CIKM, ECIR, ICTIR, SIGIR, WSDM, and TheWebConf, and has previously delivered tutorials at these venues.

6 Previous Editions

We presented an earlier version of this tutorial at SIGIR 2025, with around 25 people attending. The tutorial slides and materials are provided on the website https://economic-fairness-ir.github.io/. Compared to the previous version, the tutorial has been updated to include the latest research on unfairness [16, 46] presented at recent conferences such as SIGIR and KDD. In addition, we have incorporated more economic examples to help participants better grasp key concepts and algorithms.

7 Materials

Slides. The slides for this tutorial will be released on the tutorial website https://economic-fairness-ir.github.io/.

Bibliography. A bibliography file will be released on the tutorial website https://economic-fairness-ir.github.io/.

Related benchmark. We provide a benchmark that introduces fairness-aware IR algorithms, evaluation metrics, and datasets [40], available on https://github.com/XuChen0427/FairDiverse.

8 Video Teaser

We have uploaded a 3-minute video to introduce our tutorial at https://youtu.be/C3hgiRVnpSI.

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