Trustworthy Algorithmic Ranking Systems

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ABSTRACT

This tutorial aims at providing its audience an interdisciplinary overview about the topics of fairness and non-discrimination, diversity, and transparency as relevant dimensions of trustworthy AI systems, tailored to algorithmic ranking systems such as search engines and recommender systems. We will equip the mostly technical audience of WSDM with the necessary understanding of the social and ethical implications of their research and development on the one hand, and of recent ethical guidelines and regulatory frameworks addressing the aforementioned dimensions on the other hand. While the tutorial foremost takes a European perspective, starting from the concept of trustworthy AI and discussing EU regulation in this area currently in the implementation stages, we also consider related initiatives worldwide. Since ensuring non-discrimination, diversity, and transparency in retrieval and recommendation systems is an endeavor in which academic institutions and companies in different parts of the world should collaborate, this tutorial is relevant for researchers and practitioners interested in the ethical, social, and legal impact of their work. The tutorial, therefore, targets both academic scholars and practitioners around the globe, by reviewing recent research and providing practical examples addressing these particular trustworthiness aspects, and showcasing how new regulations affect the audience's daily work.

CCS CONCEPTS

• **Information systems** → **Recommender systems**; **Document filtering**; • **Applied computing** → *Law, social and behavioral sciences.*

KEYWORDS

recommender systems, information retrieval, web search, ranking, ethics, regulation, fairness, non-discrimination, diversity, transparency, explainability

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1 INTRODUCTION

Algorithmic ranking systems researched in the fields of information retrieval (IR) and recommender systems (RSs) affect many aspects of our daily lives, deciding which content we are exposed to on the web or social media platforms, which products to buy, or which music to listen to. With the ever increasing adoption of — mostly opaque — machine and deep learning technology in such systems, many concerns about their trustworthiness have emerged. In particular, questions related to *fairness*, *non-discrimination*, *diversity*, and *transparency* have recently been in the focus of the public debate as well as discussed in many recent research articles, e.g., [4, 8, 9].

Since the aforementioned issues in algorithmic ranking systems affect and are influenced by many stakeholders, e.g., researchers, developers, end users, service providers, policymakers, and economists, they call for an interdisciplinary treatment, involving the disciplines of artificial intelligence, computer science, ethics, law, and politics, just to mention a few. Acknowledging these facts, the tutorial takes an interdisciplinary approach. Nevertheless, we particularly tailor our discussion of these topics to the WSDM community, especially experts in web search and recommender systems.

The tutorial is supported by a GitHub repository, containing the tutorial slides with references to all discussed research: https://github.com/socialcomplab/Trustworthy-ARS-Tutorial-WSDM22.

2 TOPICS

The tutorial addresses *trustworthy AI* with a focus on fairness and non-discrimination, diversity, and transparency in algorithmic ranking systems in an interdisciplinary manner. The concept of trustworthy AI was proposed in 2019 by the High Level Expert Group appointed by the European Commission and composed of experts from academia, industry and civil society. Their *Ethics Guidelines* define seven key requirements that AI systems should meet in order to be trustworthy [12]: (1) human agency and oversight; (2) technical robustness and safety; (3) privacy and data governance; (4) transparency; (5) diversity, non-discrimination, and fairness; (6) societal and environmental well-being; and (7) accountability.

Fairness and non-discrimination: The discussion has been fueled by findings of recent studies that identified harmful biases in data, algorithmic behavior, and corresponding lists of retrieved documents and recommended items, e.g., [5, 13, 19, 20, 23, 33, 44]. These biases can result in unfair treatment or even discrimination against certain users or groups of users, e.g., with respect to their gender [19], age [35], or personality traits [25]. In some, but not all, cases such algorithmic behavior is illegal [9, 42].

Diversity: Studies have shown the value of diversity to improve innovation and excellence in research [39]. In the context of AI, several policy reports and experts [12, 41] have suggested incorporating diversity in the development process. Diversity refers to the existence of variations of different characteristics among individuals, such as gender, age, race, religion, or cultural background, being related to the fairness principle mentioned above. Retrieval and recommender systems should then incorporate a diversity of perspectives in research and development (e.g., through diverse research communities [11], developing teams or user groups) and make sure that developed technology provides an equal outcome for all potential stakeholders. Note that this does not only apply to the research communities and development teams, but in an IR and RSs context also to content producers (e.g., diversity of authors of web documents that are retrieved, or music artists whose songs are recommended).

Transparency: Transparency has been defined as a means for trust in technology and involves different concepts such as explainability, traceability, and communication [12, 37, 38, 43]. Explainability concerns the ability to explain the technical process of an AI system (i.e., provide the means for humans to understand and trace the outputs of the system) and the related human decisions (e.g., application domain or task to be solved), e.g., [29, 40]. These explanations should be adapted to different expertise levels, from developers to end users of the system. The related concept of justification refers to the requirement of a retrieval or recommendation system, in our case, to justify why a certain document or item was presented to the user, e.g., [1, 6]. Traceability allows keeping track of the behavior of a system in a chronological way, and facilitates auditability, i.e., the ethical assessment of algorithms to investigate potentially harmful consequences such as if an algorithm is biased or exhibits discriminatory behavior [2]. Finally, the concept of communication incorporates the idea of documenting the system development process, capabilities, and limitations [27, 31].

The importance of these topics is further highlighted by many recent guidelines, regulations, and policies, as discussed in [8, 30]. For instance, in the EU context, we can rely on the *EU Charter of Fundamental Rights*[1] [10], *EU Ethical Principles for Trustworthy AI*[2] [12], *Regulatory Framework for AI*,[3] and the *Digital Service Act*[4], which all strongly refer to retrieval and recommendation systems. In the US context, the *Platform Accountability and Transparency Act* (PATA),[5] proposed by several US senators, requires large platforms to make data available to support scientific research and oversight connected to data-driven algorithms; and California recently released a *Regulation on Automated Decision Systems for Employment and Housing*.[6] The Chinese government has recently rolled out several documents on governance of AI technology.[7]

[1]https://ec.europa.eu/info/aid-development-cooperation-fundamental-rights/your-rights-eu/eu-charter-fundamental-rights_en
[2]https://op.europa.eu/en/publication-detail/-/publication/d3988569-0434-11ea-8c1f-01aa75ed71a1
[3]https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai
[4]https://digital-strategy.ec.europa.eu/en/policies/digital-services-act-package
[5]http://www.coons.senate.gov/download/text-pata-117
[6]https://www.dfeh.ca.gov/wp-content/uploads/sites/32/2022/03/AttachB-ModtoEmployRegAutomated-DecisionSystems.pdf
[7]https://carnegieendowment.org/2022/01/04/china-s-new-ai-governance-initiatives-shouldn-t-be-ignored-pub-86127

3 FORMAT AND ORGANIZATION

The tutorial is organized into five parts: an introduction including ethical guidelines for trustworthy AI and their adoption in regulatory approaches; three subsequent parts corresponding to the main themes addressed, i.e., fairness and non-discrimination, diversity, and transparency; and a discussion of open challenges. Throughout the three main parts, we discuss three perspectives: the system-centric perspective, the human-centric perspective, and the legal perspective, covering technical aspects, human needs, and legislators' points of view, respectively. More precisely, the tutorial covers the following aspects and is organized accordingly:

(1) **Introduction**
We provide details on the tutorial background, motivation, objectives, relevance for the scientific community, and recent political and legal regulations.
  (a) *Ethics guidelines for trustworthy AI*: We introduce the seven requirements for trustworthy AI and how they relate to ranking systems, in particular IR and RSs. We provide examples of related scientific publications and outline the specific challenges that need to be addressed.
  (b) *From ethics guidelines to regulatory approaches: an EU perspective.* We discuss the translation of ethics guidelines to legal requirements, with a focus on current EU regulations, in particular the *AI Act*[8] and *Digital Services Act.*[9]

(2) **Fairness and Non-discrimination**
  (a) *Stakeholders:* We discuss the various stakeholders of retrieval and recommender systems, approaching the question for whom the system should be fair.
  (b) *Definition and quantification of bias and fairness:* We introduce the various kinds of bias and fairness concepts and definitions that are relevant for IR and RS research, along different axes (e.g., societal vs. statistical biases, model vs. presentation bias, provider vs. consumer fairness); we review the most common measures and metrics to quantify bias and fairness; we discuss their relation to political and legal regulations.
  (c) *Algorithms to mitigate biases and improve fairness:* We categorize the main strategies to mitigate harmful biases and improve fairness of retrieval and recommender systems, e.g., into pre-, in-, and post-processing techniques; we present concrete methods for each of these categories.
  (d) *Technical versus ethical and legal perspectives:* We discuss how the regulatory and legal frameworks align with the operationalization of fairness according to formal definitions often found in IR and RS research.

(3) **Diversity**
  (a) *Categories of diversity:* We introduce and discuss various kinds of diversity, i.e., personnel diversity in the research community and development teams, but also diversity in terms of the creators of content that can be retrieved or recommended.
  (b) *Diversity axes:* We elaborate on important groups or axes of diversity, including adults to children (age), from men to women to diverse genders, from western to non-western

[8]https://artificialintelligenceact.eu
[9]https://digital-strategy.ec.europa.eu/en/policies/digital-services-act-package

(culture), minority groups (e.g., indigenous people) and scientific disciplines.
   (c) *Diversity in the research community:* We present statistics of diversity aspects in the IR and RS communities, and ideas how to increase diversity.
   (d) *Integrating diversity in evaluation:* We present strategies for considering diversity in the evaluation of IR and RS algorithms, in terms of adopted metrics, participants in user evaluations, and perspectives.

(4) **Transparency**
   (a) *Categories of transparency:* We introduce the major aspects of transparency, as they relate to building trust in IR and RS technology; we focus on explainability, traceability, and communication; we review and clarify the terminology.
   (b) *Explainability and justification:* We discuss major strategies to achieve explainability of IR and RS technology, i.e., provide means to understand how the system works, targeting different stakeholders (e.g., developers vs. end users); we review approaches to provide justifications, i.e., mechanisms for the system to justify why a system outputs a certain (list of) documents or items.
   (c) *Traceability and auditability:* We discuss strategies to keep track of the behavior of a system in a chronological way, in particular with the aim of facilitating auditing. We also point to recent works that discuss legal groundings and consequences of algorithmic auditing approaches, which is an under-researched topic to date [26].
   (d) *Communication and logs:* We discuss the importance of documenting the development process, the resulting models, system capabilities, intended use, and limitations.

(5) **Open Challenges**
   (a) Understanding the discrepancy between (1) bias, fairness, and diversity metrics, (2) human perception of these aspects and factors influencing this perception, and (3) regulatory frameworks.
   (b) Understanding the capabilities and limitations of existing technical solutions in terms of fairness, diversity, and transparency.
   (c) Taking a multistakeholder perspective when developing solutions for fairness, diversity, and transparency in IR and RS technology.
   (d) Improving the communication between the different stakeholders and between relevant research communities, including computer science, law, ethics, economy, sociology, psychology, in order to foster interdisciplinarity.

4 BIOGRAPHIES OF PRESENTERS

Markus Schedl (http://www.mschedl.eu) is a full professor at the Johannes Kepler University Linz (JKU), affiliated with the Institute of Computational Perception, leading the Multimedia Mining and Search group. In addition, he is head of the Human-centered AI group at the Linz Institute of Technology (LIT) AI Lab. His main research interests include recommender systems, user modeling, information retrieval, machine learning, multimedia processing, and trustworthy AI, with a particular focus on detecting and mitigating bias in retrieval and recommendation algorithms [20, 24, 25, 33] and on psychological models for recommendation [21, 22, 32]. He (co-)authored more than 240 refereed conference papers, journal articles, and book chapters. He has already given numerous tutorials in top venues including *ACM SIGIR* (2022 on " Retrieval and Recommendation Systems at the Crossroads of Artificial Intelligence, Ethics, and Regulation"), *ACM Recommender Systems* (2018 on "New Paths in Music Recommender Systems Research" and 2022 on "Psychology-informed Recommender Systems"), and the *ACM Web Conference* (2018 on "Complex Recommendations" and 2022 on "Psychology-informed Recommender Systems: A Human-centric Perspective on Recommender Systems").

Emilia Gómez (https://emiliagomez.com) holds BSc and MSc degrees in Electrical Engineering and a PhD degree in Computer Science. She is a principal investigator on Human and Machine Intelligence (HUMAINT) at the Joint Research Centre (European Commission). She is also a guest professor at the Music Technology Group, Universitat Pompeu Fabra, Barcelona. Her research is grounded in the Music Information Retrieval field, where she has developed data-driven technologies to support music listening experiences. Starting from music, she studies the impact of artificial intelligence (AI) on human decision making, cognitive and socio-emotional development. Her research interests include fairness and transparency in AI, the impact of AI on jobs, and how it affects children development. She is currently a member of the Spanish National Council for AI and the OECD One AI expert group.

Elisabeth Lex (https://elisabethlex.info) is an associate professor and principal investigator of the Recommender Systems and Social Computing Lab at Graz University of Technology (TUG). Her research interests include recommender systems, user modeling, information retrieval and computational social science, with a particular focus on psychology-informed recommender systems [14, 15, 17, 21, 22, 32, 36], bias in recommender systems [18, 20], human decision making and recommender systems [3, 7], privacy in recommender systems [28], or music consumption [16, 34]. Elisabeth has (co-)authored more than 120 peer-reviewed publications in the aforementioned topics. She has given tutorials on "Psychology-informed Recommender Systems" at the 11th Italian Information Retrieval Workshop (IIR) 2021, at the Complex Networks and their Application conference 2021, at the 7th ACM SIGIR Conference on Human Information Interaction and Retrieval (CHIIR) 2022, and at The ACM World Wide Web conference 2022.

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