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Abstract

This deliverable constitutes a comprehensive survey of the literature on mitigating algorithmic bias. It represents the synthesis of all the work carried out in WP3. The survey develops a conceptual framework for understanding the problem and solution spaces of algorithmic bias, as well as the roles of various stakeholders. The manuscript was prepared as a submission to the journal ACM Computing Surveys.

Keyword(s):	Algorithmic bias, ACM Computing Surveys, conceptual framework, literature review

Contents

1. Executive Summary

D3.4 is a survey paper detailing our understanding of the state-of-the-art in the emerging field of *Mitigating Bias in Algorithmic Systems*, based on 12 months of intensive, collaborative work with the existing published literature. Mitigating bias in algorithmic systems is a critical issue drawing attention across communities within the information and computer sciences. Given the complexity of the problem and the involvement of multiple stakeholders – including developers, end-users and third-parties – there is a need to understand the landscape of the sources of bias, and the solutions being proposed to address them. This deliverable provides a "fish-eye view" examining approaches across four areas of research: machine learning (ML), human-computer interaction (HCI), recommender systems (RecSys), and information retrieval (IR).

The literature describes three steps toward a comprehensive treatment – bias detection, fairness and explainability management – and underscores the need to work from within the system as well as from the perspective of stakeholders in the broader context. The survey aims to help the reader achieve a high-level understanding of the current state of bias in algorithmic systems across the four domains and to describe opportunities for cross-fertilization between communities. It presents a fish-eye view of the literature surrounding algorithmic bias, its problem and solution spaces in order the user to maintain perspective of the "big picture", but can still choose when to drill down into further details.

2. Problem Space

Fig. 1 provides a general characterization of an algorithmic system, with its macro components, which we have used to examine the problem space of algorithmic bias. In this generic architecture, the system receives input (I) for an instance of its operation. This is provided by a user (U), or another source (e.g., the result of an automated process). The algorithmic model (M) makes some computation(s) based on the inputs and produces an output (O). The model learns from a set of observations of data (D) from the problem domain. It may also receive constraints from third-party actors (T) and/or internal fairness criteria (F) which modify the operation of the algorithmic model (M). Finally, some systems have direct interaction with a user (U) who, as previously discussed, will bring her own knowledge, background and attitude when interpreting the system's output.

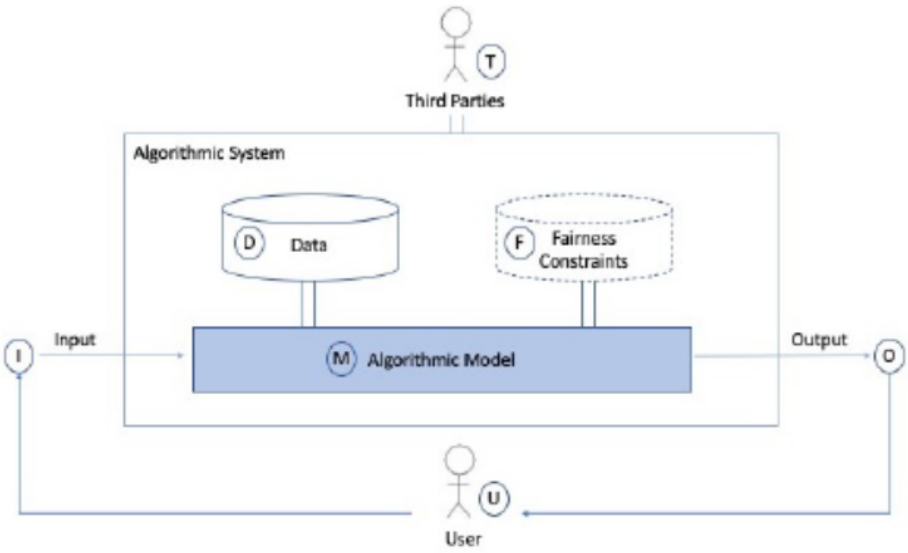

Fig. 1: Generic architecture of an algorithmic system

Thus, bias may manifest and/or be detected in one or more of these components:

- Input (I) - Bias may be introduced in the input data, e.g., as incorrect or incomplete information input by the user.
- Output (O) - Bias may be detected at the outcome (value(s)/label(s)) produced in response to the input.
- Algorithm (M) - Bias can manifest during the model's processing and learning.
- Training Data (D) - Training data may be inaccurate, imbalanced, and/or unrepresentative. Furthermore, it may contain information about sensitive attributes of people.
- Third Party Constraints (T) – Implicit and explicit constraints, given by third parties, may impact the design and performance of the algorithm and cause discrimination and fairness issues. These include operators of the system, regulators and other bodies that influence the use and outcomes of the system.
- Fairness Constraints (F) – Fairness constraints may be introduced within the system, such that one interpretation of fairness is prioritized over others.
- User (U) – When users interact directly with a system, they may contribute to bias in a number of ways, such as through the inappropriate use of the system or misinterpretation of the system's output.

The problematic components and/or points at which bias can be detected are also shown in Fig. 2, which groups them into four main types: data bias, user bias, processing bias, and human bias. In reality, all biases are at least indirectly human biases; for instance, datasets and processing techniques are created by humans. However, we believe that it is helpful to distinguish the biases that are directly introduced into the system by humans, such as third-party biases, those resulting from conflicting fairness.

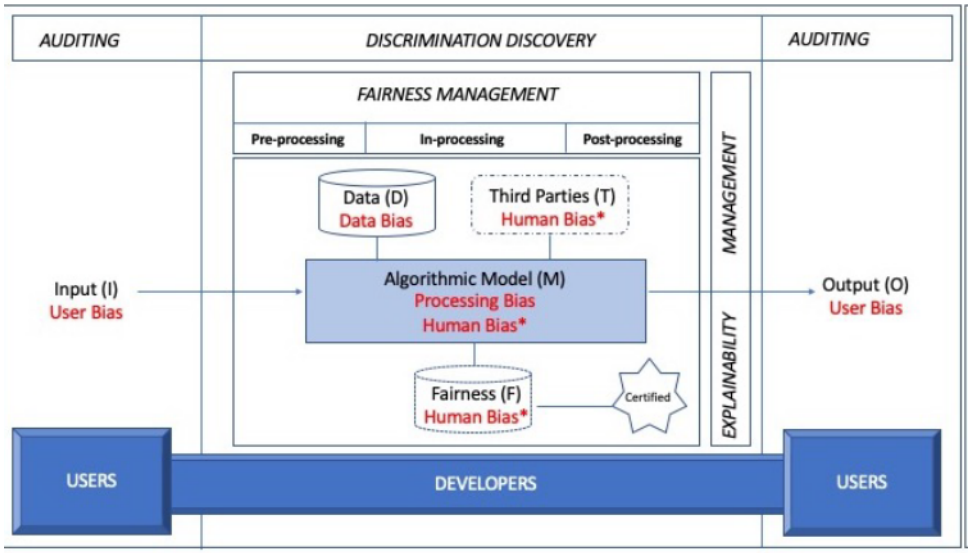

Fig. 2: Observers' fish-eye view of mitigating algorithmic bias: problems, stakeholders, solutions

3. Solution Space

The literature suggests that a comprehensive solution for mitigating algorithmic bias consists of three main steps:

- **Detection of Bias:** This involves scrutinizing the system to detect any type of systematic bias. The two main approaches for detecting bias in an algorithmic system, which are described in the literature are: Auditing and direct/indirect Discrimination discovery. As Table 1 shows, in machine learning systems, discrimination detection is mostly done by implicit/explicit discrimination discovery methods which include measuring discrimination or using a causal Bayesian network. Auditing in ML systems is mostly done by a black-box auditing software tool or when auditors search for any bias through the dataset. In IR, HCI and RecSys systems, users mostly act as auditors by submitting different queries in search engines and social networks or by taking the role of crowdworker in the crowdsourcing conducted studies.

Domain	Problem	Solution	Reference(s)
		Detection of Bias	
ML	Data/Model Data/Model	Auditing	Situational and testing auditing [91, 159] Automatic auditing tool [121]
ML	Data/Model/Output	Discrimination Discovery	Direct/Indirect [28, 32, 87, 108, 155, 159, 164]
IR	User	Auditing	User acts as auditor [65, 73, 83, 86, 93, 104, 142]
IR	User/Data User/Output	Discrimination Discovery	Direct/Indirect [8, 24, 41, 89, 106, 144, 147–149, 154] Perceived Bias[6, 66, 145, 146]
HCI	User/Data	Auditing	Auditing system[69, 95]
HCI	Third Party/Model/Output	Discrimination Discovery	Direct/Indirect [7, 31, 53, 110]
RecSys	Data/Output	Auditing	Auditing system [39, 44]
RecSys	Data/Output	Discrimination Discovery	Direct/Indirect [3, 10, 42, 131, 134]

Table 1: Summary of the problem and bias detection solution space per domain

- **Fairness Management:** includes the techniques developers use to mitigate the detected bias and certify that the system is fairness-aware. Fairness management approaches can be classified into: Fairness sampling (or pre-processing), Fairness learning (or in-processing) and Fairness certification (or post-processing methods). Pre-processing methods handle bias in input data, in-processing methods concern the mitigation of bias in the algorithm and post-processing methods concern the elimination of bias in the outcome. As displayed in Table 2, in machine learning algorithmic systems, data mining techniques are used to mitigate bias either in the data, in the model processing or at the outcome decision. User-focus systems such as information retrieval, recommender systems and human-computer interface systems use mostly pre-processing approaches such as fairness sampling and feature selection to handle bias in data.

Domain	Problem	Solution	Reference(s)
		Fairness Management	
ML	Data	Fairness Sampling	Pre-processing methods [18, 68, 70, 85, 159]
ML	Model	Fairness Learning	In-processing methods [21, 35, 54, 71, 75–77, 84, 151, 157]
IR	Data	Fairness Sampling	Pre-processing methods [34, 36, 52, 127]
IR	User/Model	Fairness Learning	In-processing methods [62, 96, 100]
HCI HCI	Data User/Model	Fairness Sampling Fairness Learning	Pre-processing methods [69] In-processing methods [16, 74, 122]
RecSys	Data	Fairness Sampling	Pre-processing methods [72, 91]
RecSys	User/Model	Fairness Learning	In-processing methods [23, 82, 98, 130, 152, 156]
ML	Model/Output User/Output	Fairness Certification	Post-processing methods [58, 70, 108] Perceived fairness management [132]
IR	User	Fairness Certification	Raise user awareness[43]
HCI	User/Output	Fairness Certification	Perceived fairness management [88, 150]

Table 2: Summary of the problem and fairness management solution space per domain

- **Explainability Management:** is applied to the system to facilitate transparency and to build trust between Observers/Users and the system. Explainability approaches have primarily been developed in the context of ML algorithms and systems. However, there is a growing literature within the HCI and IR communities. These works suggest that explainability and judgement of the outcome or decision of the system should be provided in order to enhance the trust of the end user in the system. As displayed in Table 3, in ML systems, the explainability method is usually based on the algorithm used in the system, considering whether it is an interpretable algorithm (white-box) or a black-box model such as deep learning. The explainability approaches also concern either the explainability of how the algorithm works or of the algorithm's outcome. There are also the model-agnostic explanation approaches that explain the output of any classifier, regardless of the machine learning algorithm used to train it. Finally, explainability approaches have also been widely discussed in recommender systems. The difference between these approaches and the ones used in ML are that they take into consideration the user's perception and specific goal of increasing the trust of the end-user in the system. In RecSys literature, various explanation styles have been reviewed according to the purpose of providing explanations in a recommender system e.g., transparency, scrutability, trust, etc.

Domain	Problem	Solution	Reference(s)
		Explainability Management	
ML	Model	Black-box Expainability	Model Explainability [15, 26, 37, 51, 81, 124, 161] [20, 30, 60, 67, 90, 135, 136, 141, 162]
ML	Output	Black-box Explainability	Outcome Explainability [32, 55, 109, 113, 113, 114, 133] [12, 47, 59, 125, 129, 139, 153, 161, 163]
HCI	User	Black-box Explainability	Model Explainability [64]
HCI	User/Output	White & Black-box explanations	Outcome Explainability [11, 40, 49, 111]
RecSys	User/Output	Black-box Explainability	Outcome Explainability [14, 25, 80, 102, 138, 140, 143]

Table 3: Summary of the problem and explainability management solution space per domain

4. Conclusion

We provided a “fish-eye view" of research to date on the mitigation of bias in any type of algorithmic system. With the aim of raising awareness of biases in user-focused, and algorithmic-focus systems, we examined studies conducted in four different research communities: information retrieval (IR), human-computer interaction (HCI), recommender systems (RecSys) and machine learning (ML). We outlined a classification of the solutions described in the literature for detecting bias as well as for mitigating the risk of bias and managing fairness in the system. Multiple stakeholders, including the developer (or anyone involved in the pipeline of a system’s development), and various system observers (i.e., stakeholders who are not involved in the development, but who may use, be affected by, oversee, or even regulate the use of the system) are involved in mitigating bias. A Venn diagram (Fig. 3) shows the potential for cross-fertilization among the four research communities that we reviewed, in terms of realizing comprehensive solutions for mitigating bias. The interrelationship between the communities is primarily based on the stakeholders involved in implementing each solution.

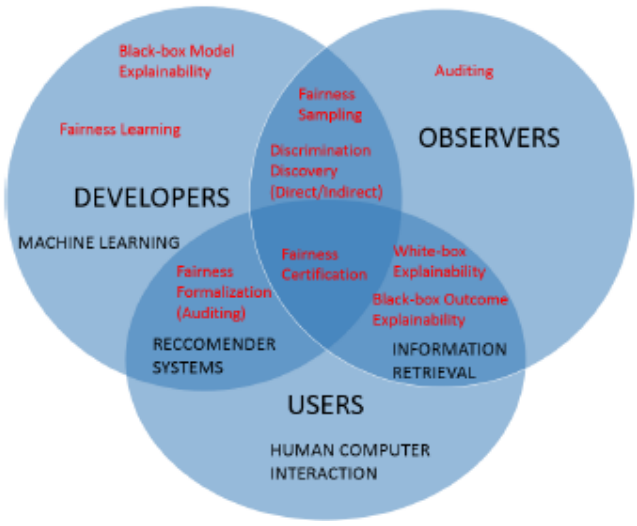

Fig 3: Venn diagram: Cross-fertilization between the four domains

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