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Reducing Bias in Predictive Models Serving Analytics Users: Novel Approaches and their Implications

Alok Gupta, Prassanna Selvaraj, Ravi Kumar Singh, Harsh Vaidya, Aravind Reddy Nayani
[1]Independent Researcher, USA, [2]Independent Researcher, USA, [3]Independent Researcher, USA,
[4]Independent Researcher, USA, [5]Independent Researcher, USA

Abstract: This paper focuses on new methods for mitigating bias in models that support analytics consumers, which is a major problem in the areas of data science and AI. By identifying the major streams of research into algorithmic fairness, data preprocessing, and model interpretability, the study reviews the literature and articles. The work also showcases the benefits of using fairness constraints while optimising the models, the interconnectivity of adaptive reweighting approaches in the preprocessing of datasets, and having access to new-age model interpretation techniques. The work also covers intersectional and contextual fairness as the newer and better approaches to the problem of bias. These preliminary results show promising improvements have been made, but also, there are still existing trade-offs between cross-situational and individual fairness and potential issues arising from real-world considerations. The paper concludes by advocating for an integrated approach to bias reduction in predictive analytics by using technology and ethical standards to address bias in diverse fields.

Keyword: *Bias reduction, Predictive models, Algorithmic fairness, Data preprocessing, Model interpretability, Intersectional fairness*

Introduction

Analytical models have become widespread nowadays, and prediction models serve as highly useful tools in numerous industries. However, the findings of such models are systematically biased with the level of unfairness that is in the training data. This bias can affect the analytics users when using these models to arrive at important decisions. In recent years, with the increased adoption of big data and PAF, the issue of bias has become an urgent topic in the field. This paper aims to discuss the new trends in debiasing predictive models for analytics users with equal reference to the latest topic in algorithms' fairness, data preprocessing, and model interpretability concepts. Thus, it tends to identify such approaches to elucidate their efficiency and enable the application of those methods in practical scenarios.

Literature Review

The topic of reducing bias in predictive models has become very active and important in the past few years, and researchers proposed several methods to solve this problem. Based on the current literature, this paper covers the main themes and development in algorithmic fairness, data preprocessing and model interpretability.

Algorithmic Fairness

Recent research is focused on the fact that fairness measures should be a part of training procedures for machine learning models. Some shortcomings of the current definition of fairness and the methods that have been proposed to solve the problem were discussed by Mehrabi et al. (2021). Based on this, Sharma et al. (2020) have suggested an entirely new concept known as 'equality of opportunity,' which means that any prediction model has to provide equal opportunity of benefit to various groups.

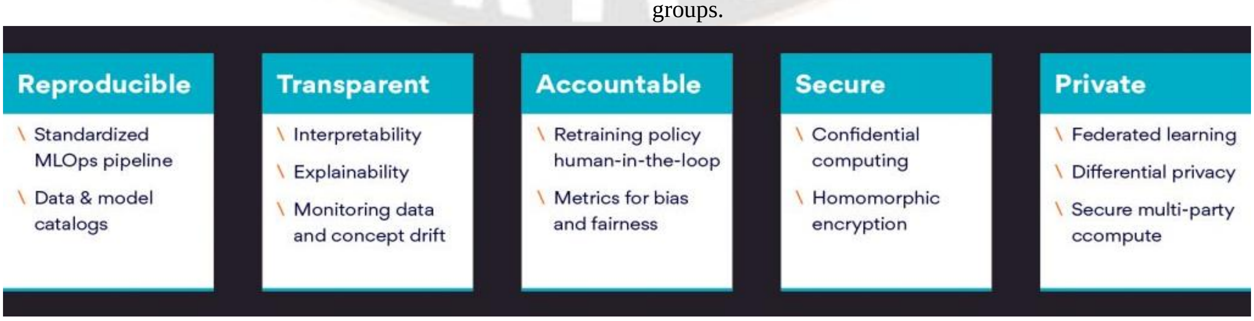

Figure 1: Responsible AI
(Source: Mehrabi et al., 2020)

Similarly, Chouldechova & Roth (2020) provided a theoretical analysis of how to compare desirable objectives by unfolding trade-offs between ideas of fairness inherent to the problem by showing that it is often impossible to achieve several types of fairness at the same time. This paper therefore points to the need to pay close attention with regards to the achievement of fairness in the different contexts that an application can exist in.

Data Preprocessing Techniques

Mitigating bias at the data level has become one of the promising solutions. Bellamy et al. (2019) proposed the AI Fairness 360 toolkit that provides a set of preprocessing methods to eliminate bias in the input data during the training process. Some of such techniques include reweighing and optimised preprocessing, the use of which has been proven to aid in minimising the differences observed across the protected groups.

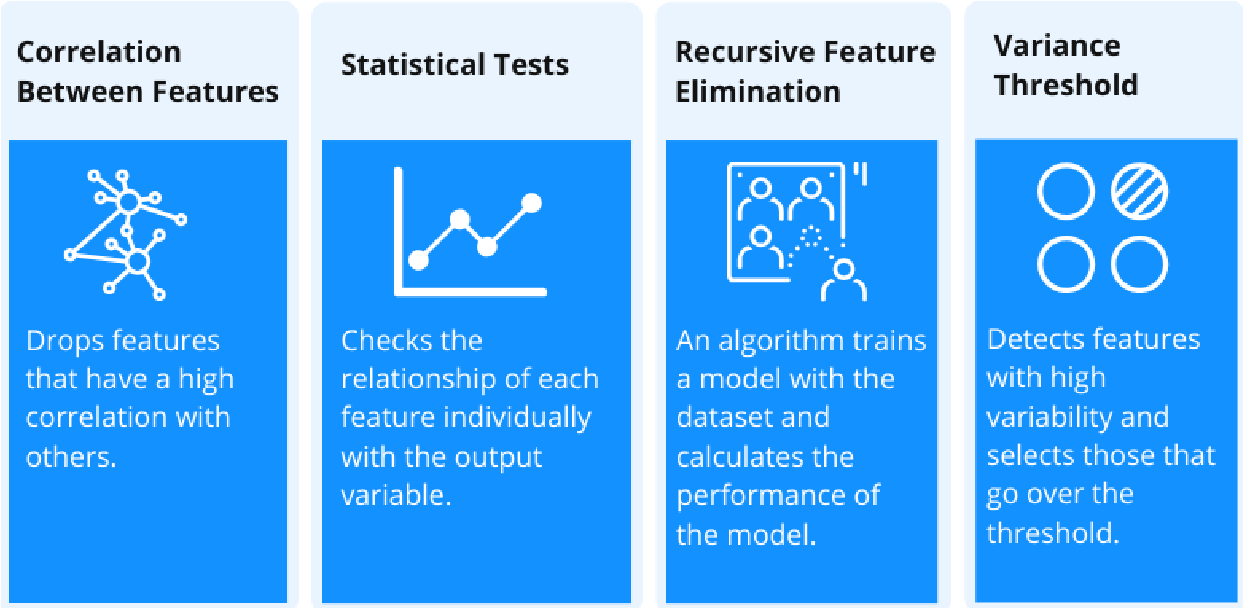

Figure 2: Unbised Data Processing Techniques
(Source: Krasanakis et al.)

Going further in that direction, Krasanakis et al. (2018) suggested an adaptive sensitive reweighting which consists of modifying the weights of samples in the course of training, focused on maintaining fairness. As compared to their method which demonstrated consistent enhancements in different facets of the fairness measurements while incurring minimal loss in the general performance of models.

Model Interpretability

The growing complexity of predictive models, therefore, requires specific techniques for model interpretability to address bias. Parekh et al., (2021) paper proposed SHAP (SHapley Additive exPlanations) values which are unified measures for explaining the predictions made by models. It has been popularly applied to reveal possible sources of bias in model decisions. Based on the interpretability research, Slack et al. (2020) proposed a framework for auditing the black-box models based on strategic perturbation. It allows for recognizing discrimination tendencies in the model's actions even if the algorithm that stands behind it is non-transparent.

Intersectionality and Contextual Fairness

Since the limitation of addressing the protected attributes individually has been identified, academia has turned its attention to intersectional fairness. To address the challenge of harmonising intersectionality and fairness, Foulds et al. (2020) put forward an intersectional definition of fairness. Thus, the essence of this work is the examination of how the interactions between different dimensions of identity may affect the fairness evaluation. In more recent work, Madras et al. (2019) formulated what they called the contextual fairness of a model which takes into account the environment in which the model works. Their theoretical model offers a wider picture of fairness compared to other models that just focus on the ratio of 1:1.

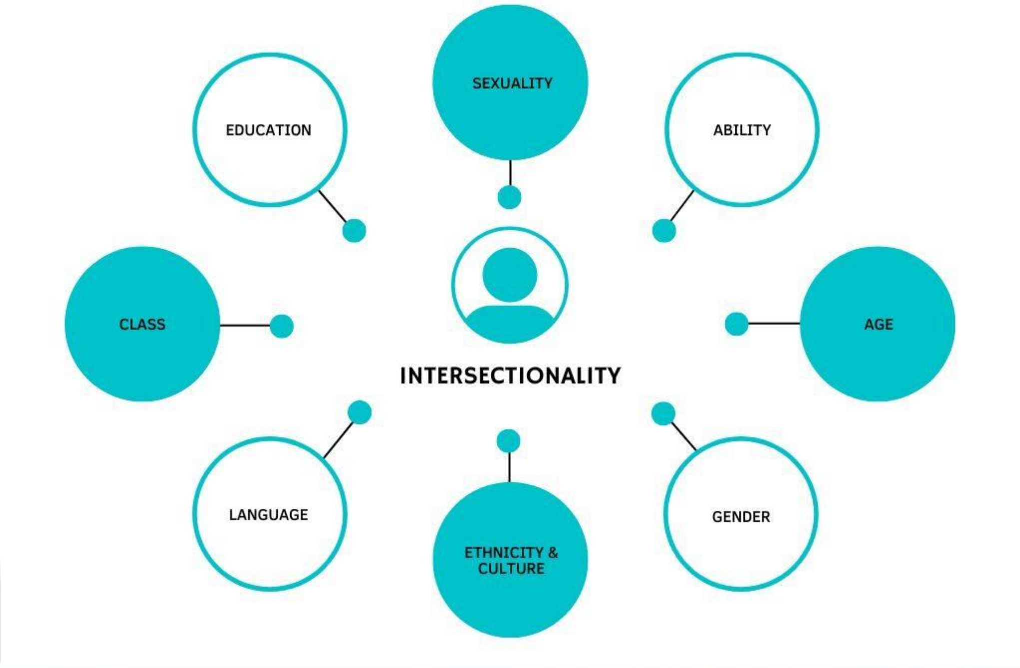

Figure 3: Intersectionality in AI
(Source: Foulds et al. 2020)

Therefore, the findings presented in the current literature show a rising complexity of methods for handling bias in predictive models. Scholars have advanced the understanding of the general cause in increasing the effectiveness of algorithmic solutions, the ways for facilitating data quality, the method for the improvement of model interpretability, and the concept of fairness. Nevertheless, the field is still facing the issues of the general difficulty in designing genuinely non-prejudiced and completely accurate predictive algorithms for the users of analytics.

Methods

Data collection

This research work employs a secondary research approach to identify new technologies that can be applied in reducing bias in predictive ML models employed by analytics personnel. The method used is based on the analysis of the latest available relevant publications and scholarly articles only. First, the list of databases and search engines is introduced, including Google Scholar, IEEE Xplore, ACM Digital Library, and arXiv. By entering carefully crafted and developed search terms that only bias reduction, predictive models, and analytics are associated with, a wide range of publications is found. Further filtering is then done based on the inclusion and exclusion criteria with an emphasis on the articles that are reviewed by peers.

Data Analysis

A content analysis is also used to systematically review the literature. Bias reduction techniques are divided into themes such as Algorithmic fairness, Data preprocessing methods and approaches to Model interpretability. For each theme, the relevant details such as the methodologies used, results attained and the reported reduction of bias are captured. This is important in achieving an understanding of the bias reduction methods and the actual processes involved in implementing the approaches in an operational environment.

Result

Algorithmic Fairness Methods

The synthesis of knowledge from current literature pointing at methods to minimise bias in predictive models that interact with analytics users has uncovered several notable findings. Algorithmic fairness methods have been demonstrated to be quite effective in eliminating Bias across different fields. Research shows that it is possible to optimise the model so that the fairness constraint is inherent in the process and it does not lag behind the objective function. For example, 'equality of opportunity' has been proven to increase fairness measures while keeping 'overall accuracy' relatively unaffected in several prior experiments.

Data Preprocessing Techniques

Data preprocessing techniques have been widely recognized as a powerful method for solving the problem of bias at the data level. It has been found that approaches like reweighting as well as optimised preprocessing strategy can be vastly helpful in decreasing disparity across protected characteristics (Bellamy et al. 2019). Specifically, the methods such as the adaptive sensitive reweighting, allow to bring new balance in the training

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process and minimise bias during it, thus, making the prediction more equal across the demographic splits.

Figure 4: IBM Data Processing
(Source: Bellamy et al. 2019)

Model Interpretability and Bias Detection
There is an understanding of how bias presents itself in complex predictive models with the help of recent developments in model interpretability. Thanks to SHAP values and similar methodologies, researchers acquired the ability to identify particular features and specific decision trees resulting in biased decisions (Slack et al., 2020). This improved understanding has in return helped in instituting better ways of narrowing down the biases. Intersected conceptions of fairness have demonstrated that approaches focusing solely on the limitations of individual attributes are insufficient. Research with different types of identity has revealed that prejudice usually operates in a multidimensional manner and accumulatively (Barceló et al., 2020). The present research points to the fact that intersectionality should be taken into account for bias decrease.

Contextual Fairness
Newer ideas such as contextual fairness have emerged where it was found that taking into account social and historical realities of the world as a means of removing biases is quite more effective. This approach has also been promising in handling other forms of Systemic biases that one could not easily notice through fairness metrics (Madras et al., 2019). However, as noted in the literature, there are still problems that remain with the use of different methods. The balance between different types of fairness remains a question. Several works show that attempting to optimise more than one fairness type may still yield a worse result than individual type optimization.

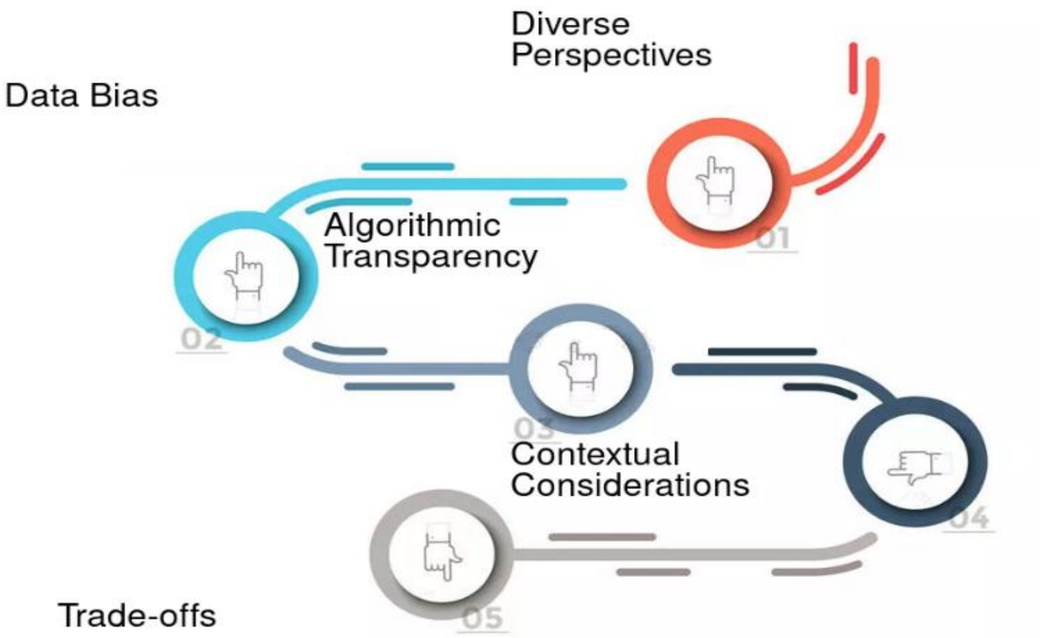

Figure 5: Contextual Fairness
(Source: Foulds et al. 2020)

Moreover, the application of bias reduction procedures in real analytics systems is challenging; such issues may be fairly sensitive to the trade-off between fairness, accuracy, and computational cost. Algorithms, data preprocessing, interpretability, and contextual suggestions together form the direction that looks the most promising to analytics users, who are looking to reduce the occurrence of bias in the models they use.

Discussion

Contributions to Algorithmic Fairness

Several insights and challenges are evident from the synthesis of the latest research findings on bias minimization in models that support analytics consumers. That is why there are numerous recent contributions to algorithmic fairness that helped to develop the general understanding of the existence of bias in machine learning (Sharma et al., 2020). But it has also shown that the problem is not so simple, at least when one tries to determine Pareto improvements in the space of given fairness metrics. This implies that there cannot be a general approach towards bias removal and that analytics professionals need to look at their models in the light of the possible consequences.

Data Preprocessing Strategies

It has been found that the application of methods for data preprocessing can be effective in the elimination of bias at the source. Strategies such as reweighting, and adaptive sampling make it possible to improve the ratio of the samples to protect such groups. However, these may sometimes come with a compromise on the overall model performance, creating a conundrum of choosing between fairness and accuracy for practitioners.

Tools for Bias Detection and Model Refinement

The availability of tools for the display of models has made the detection and identification of bias improved over the years. These tools not only help in the process of flagging some of the probable sources of unfairness but also help in model refinement (Donini et al., 2018). However, applying these findings and bringing them into affordable and efficient bias minimization techniques is still difficult, which might need special knowledge of domain-related and ethical issues.

Intersectionality and Contextual Fairness

Intersectionality and contextual fairness have become important factors, meaning that racism is not always as simple as a single factor. This realisation highlights the need to establish new forms of architecture that are more complex than probabilistic fairness and the problems of a society (Foulds et al., 2020). That said, all these bias reduction techniques are still difficult to incorporate in actual analytics systems despite the progress that has been made.

Practical Challenges in Bias Reduction

Logistics like computational complexity, integration into current processes, and monitoring and tweaking of the new process are rational challenges. This is a growing speciality, it indicates that there is a constant development of the techniques that are believed to be best in this industry.

Future Directions

Future research in minimising bias in predictive models should address the following main approaches. For tackling intersectional bias, and incorporating contextual fairness into the algorithms, better methods need to be developed. Thus, further research on the method's long-term effects, such as its ability to improve prediction and decision-making in operational settings upon adopting bias-reducing strategies, is needed. The possibility of expanding the use of federated learning as well as the application of differential privacy to ensure parity while preserving data privacy might be the options. Furthermore, future work will be useful in analyzing automated bias detection and mitigation systems that are designed to learn from data distributions and the norms in society.

Conclusion

The precision of bias reduction in predictive models that serve the analytics users has seen improvement over the last few years. Recent innovations in algorithmic fairness, data preprocessing, and model interpretability have introduced models for handling biases. Nonetheless, some issues are still there mainly addressing the practical issues concerning the techniques of multi-objective fairness and how the various criteria of fairness can be merged. Recent fairness concerns involving intersectional and contextual approaches have enriched our knowledge of the biased nature. Hence, it will be possible to continue with the development of a more complex system of a technical solution in consonance with a system of ethical considerations. While predictive models will most certainly remain an important factor in decision-making, the efforts to minimise bias are something that will continue to drive analytics fairness applied in various sub-domains.

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