---
title: "Seth Hall - STOR 390 Midterm (2)"
author: "Seth Hall"
date: "2024-10-25"
output:
  pdf_document: default
  word_document: default

---
title: "Seth Hall - Midterm 1"
author: "Seth Hall"
date: "2024-09-23"
output: pdf_document

Adressing Bias in Healthcare Algorithms: A Fairness Analysis of Predictive Models

Introduction

Prediction algorithms are becoming more and more prevalent and important in many different areas of healthcare such as decision-making, prioritizing patients, allocating resources, and even diagnosing conditions. However, as they do become more and more prevalent, more concerns are being raised about their fairness and whether they reflect or amplify existing societal biases. Many studies have shown that algorithms can unintentionally lead to unequal access to care. This especially has negative consequences for marginalized groups. This includes underrepresented racial demographics and low-income patients. These types of decisions have life-altering implications, so addressing such biases is particularly urgent.

A study titled "Dissecting racial bias in an algorithm used to manage the health of populations" by Obermeyer et. al. that unearthed significant racial disparities within a widely used predictive model, the name of which wasn't mentioned. The model in question used medical spending data from the past as a proxy for health needs, and the study by Obermeyer et. al. found that this decision led to the underestimation of health needs for black patients compared to white patients. Through statistical measures of fairness, Obermeyer et al. demonstrated the model’s systematic bias and provided quantitative proof of how these algorithms could reinforce healthcare inequities.

Summary of Method

The model that was analyzed in the study was intended to predict patient healthcare needs based on their historical healthcare spending. The objective of Obermeyer et. al.

was to determine whether fairly represented patients from different racial groups. Specifically, the study focused on whether the model was systematically undervaluing black patients' health risks because they historically spent less on health care, which is a factor that is influenced by socioeconomic barriers to accessing care.

The study employed a large and diverse data set from U.S. hospital systems. This data set contained health metrics, demographic information, and prior healthcare spending data for patients. The authors used this data set to analyze how the algorithm distributed risk scores and whether these scores adequately reflected patients' actual health needs across racial groups. Healthcare spending was used as a primary variable, and because of this it favored people who had a history of higher spending on healthcare, which tended to correlate with white patients who have historically had better access to healthcare than black patients.

To evaluate fairness within this model, the researchers implemented several key measures of fairness that have been discussed in STOR 390, including statistical parity, equalized odds, and disparate impact. These measures of fairness allowed the study to quantify the bias in the algorithm's predictions. This made the disparities not only visible, but also mathematically demonstrable.

The first fairness measure applied was statistical parity. Statistical parity is a method that adjusts data so that decisions are made fairly without discrimination, with the goal of ensuring the same probability of inclusion in the positive predicted class for each sensitive group. In this case, the sensitive groups were patients that were identified as "high-risk." In the context of this study, statistical parity would imply that black and white patients with similar medical conditions should have an equal probability of being flagged for high-priority healthcare. The researchers found that the model didn't meet statistical parity because black patients were less likely to be assigned high-risk scores compared to white patients, even if they had similar health profiles. The model clearly demonstrated imbalance because patients from different racial groups received unequal outcomes based on historical spending rather than actual health needs. This was a crucial first step in highlighting the model's inequitable outcomes.

The next measure of fairness that the researchers applied was an equalized odds test. Equalized odds tests examine the error rates of a model across different groups, specifically comparing false positive and false negative rates. Equalized odds is especially important in healthcare because an error in classification can lead to misallocation of care. For example, a false positive where a patient that doesn't have a condition tests positive for it may cause unnecessary allocation of medicine that could cause the patient harm while also taking it away from another patient who may have actually needed it. Obermeyer et al. found a statistically significant disparity in the false negative rates between black and white patients. Black patients were often categorized as low-risk, even when their health needs were comparable to those of white patients who received high-risk scores. This unequal error distribution highlighted the model's tendency to under-serve black patients. Because of this, the model failed to meet the equalized odds fairness measure.

The third measure of fairness the researchers used was a disparate impact analysis. Disparate impact is a practice that negatively affects a protected group of people more than another, even though the rules appear neutral. Disparate impact is determined by calculating the ratio of favorable outcomes across demographic groups and assessing whether this ratio remains within a specified threshold. In their analysis, Obermeyer et al. observed a marked disparate impact against black patients. Black patients were less likely to be identified as high-risk than white patients with similar medical needs. By using relative risk ratios, the researchers showed that black patients' risk scores were 48% lower than those of White patients with similar health profiles on average. Black patients with comparable needs to white patients were consistently deprioritized because they historically spent less on healthcare. This highlights a clear bias in how the model assigned risk scores.

Results

Through statistical analysis and measures of fairness, the researchers could determine that black patients were systematically assigned lower health risk scores. The difference was not only statistically significant but reproducible. This is an important aspect of the study's reproducibility. Using subgroup analysis and effect size calculations, Obermeyer et. al. demonstrated the algorithm's impact with a lot of clarity. Unlike the black boxed COMPAS algorithm that has been discussed in STOR 390, Obermeyer et. al. made their methods, data, and sources accessible, allowing other researchers to verify or add onto their findings. The study's reproducibility is important because it enables the healthcare community to examine the bias within this predictive model and potentially others.

Normative Concern

The normative implications of this study are profound. Algorithmic bias in healthcare extends beyond statistics to ethical issues with extreme real-world consequences. Not only do biased algorithms reflect existing disparities between groups, but they cause them to grow over time. From an ethical standpoint, fairness in healthcare algorithms used for prediction is essential to prevent the continuation of historical biases. In the model studied by Obermeyer et. al., the using healthcare spending as a proxy for need negatively affected patients from underserved communities. And, due to structural inequities, had limited access to healthcare and lower spending histories. This choice of proxy introduced an indirect form of discrimination, by which a neutral factor like spending became a determinant of care.

The implications are clear that healthcare providers and policymakers need to carefully evaluate the variables used in predictive models like this one. It's important so that they genuinely reflect health needs instead of reinforce socioeconomic biases. This study highlights the moral obligation to include fairness into healthcare algorithms, and it calls for more accountability in how these tools are made and used.

Future Directions

The findings from Obermeyer et. al. highlight the need for policy measures to regulate healthcare algorithms, particularly concerning fairness. One potential policy solution could be mandatory audits to ensure fairness in predictive models used in healthcae. These audits would ensure that models are rigorously tested for disparate impact, equalized odds, and other fairness metrics before being used in healthcare. Moreover, policies like this could help both healthcare providers and patients understand the basis of risk assessments and how to prioritize who gets treated. Requiring algorithms to be explainable would make it easier to identify potential sources of bias and eliminate them before they continue. Additionally, funding research into alternative fairness metrics and proxy variables could provide healthcare systems with new tools to ensure that prediction models reflect true health needs rather than indirect socioeconomic factors.

Conclusion

All in all, Obermeyer and contributors' study provides a powerful demonstration of the role that the measures of fairness discussed in STOR 390 can play in identifying and quantifying biases when it comes to healthcare algorithms. By applying statistical parity, equalized odds, and disparate impact, the researchers illustrated how a common predictive model under-served black patients by relying on a cost-based proxy for health need. Their findings offer a quantitative, reproducible account of the model's bias. This highlights the necessity of implementing fairness into healthcare algorithms to prevent the perpetuation of health disparities.

The normative and policy implications of this study are far-reaching. As predictive algorithms continue to influence healthcare delivery, ensuring their fairness and accountability is becoming a larger issue in society. Policy makers, healthcare providers, and the developers of these algorithms all must recognize that fairness is not merely a technical consideration; it is a foundational principle that upholds equity in healthcare. By advancing policies that promote fairness, a healthcare system can be developed where algorithms serve all patients equitably, regardless of their background or socioeconomic status.

Obermyer, Z., Powers, B., Mullainathan, S. "Dissecting racial bias in an algorithm used to manage the health of populations." Science, Vol 366, Issue 6464. 25 October 2019. https://www.science.org/doi/10.1126/science.aax2342