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# THE CARCERAL FEEDBACK LOOP: INFORMATICS MUSINGS ON ALGORITHMIC PREDICTION SYSTEMS

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**ABSTRACT**

Using the Missingness Analysis framework from statistics and the social informatics theory of the political valence of information and sociotechnical systems, as well as publicly available crime complaint data from a US city with a history of using algorithmic policing systems. This paper seeks to investigate fairness issues in the use of historical data in predictive policing systems from a social informatics lens. Moreover, the paper critically analyses the potential consequences, implications, and limitations of historical data within its multidimensional implementation context. The paper also addresses the sustainability of the continued use of historical data in machine learning and algorithmic policing.

**Keywords**
Algorithmic policing, AI/ML, missingness analysis framework, social informatics theory

**EXTENDED ABSTRACT**

With recent advances in artificial intelligence (AI) and machine learning (ML), mathematical models in the form of automated algorithmic decision systems enable not just the discovery of patterns in large datasets, but also predictions, prognostications, and forecasts. Consequently, algorithmic decision technologies are gradually entrenched in a wide range of domains in the public sector, including algorithmic policing (AP). These automated decisions have potentially far-reaching consequences for the persons and groups served.

AI/ML technologies are touted to bring efficiency, accuracy, and eliminate human bias (Hampton, 2021; Jefferson, 2020). So far, while efficiency and accuracy might have anecdotal evidentiary support, the elimination of human bias remains a utopian dream: The new technologies are largely perceived to be exacerbating the situation, as they tend to digitalize human bias and digitally redline minority demographics, people of color (PoC), disabled persons, women, and older adults (Benjamin, 2019; Noble, 2018; Eubanks, 2016; O'Neil, 2016). This raises a plethora of ethical concerns, including fairness, inclusion, privacy, accountability, transparency, and equity.

This threat of 'algocracy' (Danaher, 2016) is a multidimensional problem with legal, contextual, political, social, economic, technological, and policy dimensions. While no technology is completely free of human bias, they can at least be fair, and fairness has become more and more nuanced and too often insufficiently addressed in discourses on algorithms, AI, ML, and predictive policing. So far, the focus of scholarship has been on conceptualizing algorithmic governance systems and demystifying the underlying algorithmic opacity, calls and prototypes for more accountability and transparency from AI/ML vendors and practitioners, and very few experimental studies on the effects of the technologies.

One critical but often neglected area in which automated decision systems are most susceptible to bias is in the quality of datasets used for training the predictive model. In AP, for instance, the predictive model is trained on past criminal complaint data to predict when and where the next crime is likely to occur, and who the likeliest perpetrators are. Thus, AP pre-emptively determines where, how, and when to deploy police resources including personnel and equipment. While statistically, more data makes for more accurate predictions, more historical data heightens the already widespread concerns that AP systems may be reinforcing historical and existing stereotypes, biases and inequities, thereby jeopardizing fairness and equity (Jefferson, 2020; Richardson et al., 2019; Ferguson, 2017; Barocas & Selbst, 2016; Collins, 2018; Angwin et al, 2016; Vagle, 2016). Moreover, historical data is perceived to be particularly susceptible to pernicious feedback loops that predispose predictive models trained on it to self-fulfilling prophecies and biased outcomes (Pessach & Shmueli, 2020, p.14; Kearns & Aaron, 2020; Moses & Chan, 2018). The outcomes of such predictions and the decisions that follow have potentially far – reaching and life- changing consequences for persons and groups disproportionally impacted.

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