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49 Sentencing and risk assessment algorithms

Abstract: Digital technologies in the form of Artificial Intelligence (AI) models, particularly machine learning algorithms, are increasingly influencing decision-making in justice systems around the world. This contribution focuses on their role in partially automating judicial decision-making. It is structured around three sections. First, it outlines the origins of the technologies and describes how they influence sentencing. Second, it considers the justifications offered by their proponents, and third, it critically explores their implications for justice, linking the analysis to discourses about their capacity to reproduce biases and their lack of transparency. Finally, the chapter provides recommendations on how best to remediate pressing challenges. Although it focuses on developments in the UK, it refers to other jurisdictions where relevant.

Keywords: Artificial Intelligence, risk assessment algorithms, predictive algorithms

Introduction

Although its definition is varied and contested, AI is commonly depicted as "general purpose digital technologies that enable machines to do highly complex tasks effectively" (Hall and Pesenti, 2017; see also Matheis and Kingdon, 2023). This definition encompasses several techniques and technologies including machine learning algorithms that predict risk of recidivism and can influence how judges evaluate risk to determine the appropriate sentence. Some of the risk assessment algorithms are basic logistic regression models which became widespread across the UK and other countries from the 1990s onwards, whilst several now rely on more advanced machine learning techniques.[1]

According to the Sentencing Council (2023) which provides guidelines on sentencing in England and Wales, "A sentence is the punishment a judge or magistrate [the sentencer] decides should be given to someone who has been convicted of a crime." Risk assessment algorithms (see Artificial Intelligence by Van Brakel) are trained to analyze data and detect patterns which inform decision-making in the context of, for example, crime risk prediction and sentencing (see Prediction by Ķīlis, Gundhus, and Galis). As advanced computational technologies, their decision-making is, so the argument goes, more objective than that of human actors, and their risk predictions can be considered during sentencing. This chapter's contribution lies in its analysis of the origins of such sentencing technologies, how they influence sentencing practices, and the

1 See Berk and Bleich (2013) for a detailed description of statistical approaches to predicting risk of recidivism.

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justifications offered by their proponents. It also provides insights on the implications of the technologies for justice and connects the analysis to discourses about their capacity to reproduce bias and their lack of transparency (see Bias by Oswald and Paul). The chapter concludes with recommendations on how best to remediate pressing challenges.

AI and sentencing

Known colloquially as risk assessment tools, risk assessment algorithms (some of which are machine learning models and are as such increasingly described as AI) are deployed in justice systems. The technologies are used at various phases of the criminal justice process including the post-conviction, pre-sentence stage when judges draw on various sources of information about a defendant to craft a sentence. Several risk assessment algorithms form part of the criminal justice AI infrastructure. They include sections of the Offender Assessment System—OASys (UK), the Correctional Offender Management Profiling for Alternative Sanctions—COMPAS (USA), the Level of Service Inventory-Revised (LSI-R) and the Level of Service/Case Management Inventory—LS/CMI (Australia, Canada, Sweden, Switzerland, and UK).

A brief history

There are similarities between the risk assessment algorithms currently playing a key role in sentencing across several Western jurisdictions and the statistical approach established by Burgess (1928) for parole decision-making. Burgess analyzed data from criminal justice populations to identify factors which he believed were linked to parole outcomes. Then, he tested the factors on a retrospective sample and used them to design a risk assessment tool for determining risks of parole violation (see also Kemshall, 2019).

In an extension of this actuarial approach to risk prediction, some of the currently used risk assessment algorithms deploy machine learning techniques including statistical methods such as logistic regression models (Kemshall, 2019; Raynor, 2019). Advanced machine learning techniques for analyzing more risk factor variables than regression models, are also used to predict crime risks (see Howard, 2017; Law Society, 2019).

Generally, the process of designing risk assessment algorithms involves training the technologies (such as a logistic regression model), using historical data, so they learn how to, (1) process data from defendants and other risk subjects, (2) detect patterns e. g., risk factors (which are sometimes pre-defined), and (3) predict risk (Moore, 2015). Such risk factors are variables said to correlate with recidivism and they include, for example, demographic information (typically, age, gender, and criminal history); socioeconomic and lifestyle factors (accommodation, educational and employment status, family relationships, leisure pursuits, alcohol, and drug misuse); attributed personality, cognitive and behavioral characteristics (behavior, thinking, attitudes) (Ministry of Justice, 2019). Individuals whose profile indicate the presence of these factors, particularly those weighted as strongly correlated with reconviction (typically within two years of completing a custodial or community sentence), will attract higher risk scores than others. The predetermined risk factors are derived from various theories. Examples are criminological and sociopsychological perspectives that depict factors such as familial and social-environmental circumstances as well as rational choice as the *causes* of recidivism (see generally, Bonta and Andrews, 2017). It is nevertheless argued that they are in fact only possible *correlates* (Prins and Reich, 2018).

Automating sentencing practice

The ways in which the risk scores produced by such digital predictive technologies influence sentencing varies across jurisdictions. In Western countries such as the UK, US, and Canada, the scores are embedded in the reports that sentencers consult to determine the appropriate sentence. In the UK, a Pre-Sentence Report (PSR) as defined by Section 158 (1) of the Criminal Justice Act 2003 and Section 31 (1) of the Sentencing Act, is written, "with a view to assisting the court in determining the most suitable method of dealing with an offender." Further, according to the UK's Sentencing Council (2023a), a fundamental role of the probation service in court is "preparing pre-sentence reports for courts, to help them select the most appropriate sentence." The reports allow the courts to meet their legal obligation to take various risks into account during sentencing.

All PSRs should outline both the risk scores ascribed to the convicted person and the recommendations of the report writer (the probation officer) regarding a sentence that is commensurate with the predicted risk. Judges are expected to consider all that information when crafting the appropriate sentence. Although further research is required, official statistics point to a high concordance between PSR recommendations and sentencing decisions: "89 % of immediate custodial sentences proposed in PSRs resulted in that sentence being given in the year ending December 2022" (Ministry of Justice, 2023).

In general, through PSRs, risk assessment algorithms provide information with which the courts can impose sentences that restrict civil rights and liberties, occasionally beyond set tariffs. In the US they can influence sentencing in capital cases (Kehl et al., 2017). Yet, the scores and classifications produced by risk assessment algorithms can never state with absolute certainty the likely or exact risk posed by an individual. A risk score only ever indicates that some people fitting a certain profile may reoffend and cannot categorically conclude that the defendant is one of those who will (see Hamilton and Ugwudike, 2023). A reason for this is that risk assessment algorithms predict individual risk on the basis of risk factors derived from statistical analysis of data from various sources including criminal justice populations (see, for example, Howard and Dixon, 2012). This lack of individualization heightens the probability of unfair profiling. In short, the algorithms generate predictions about group risks not individual risk. Yet, they are used for the latter in high stakes sentencing processes.

Implications of AI-driven sentencing: claims and counterclaims

The high level of mathematical quantification underpinning predictive algorithms such as OASys (UK) and COMPAS (US), create a veneer of scientific objectivity that ostensibly transcends professional judgment which has long been depicted as fundamentally prone to biases and prejudices (Grove and Meehl, 1996). Indeed, proponents and state procurers of predictive algorithms typically emphasize their value and prospects, using optimistic frames which depict them as capable of analyzing large-scale data objectively whilst reducing human bias, optimizing cost-effective resource allocation, and enhancing institutional efficiency (see Huq, 2019; Lavorgna and Ugwudike, 2021). Nevertheless, predictive algorithms pose challenges for justice. This chapter now explores the problems of bias and lack of transparency, both of which undermine key antecedents of justice, particularly non-discriminatory practice and procedural due process.

Racial bias

While there are several potential conduits of bias, a main source is the type of data on which the algorithms rely for prediction. An example is administrative data on criminal justice populations, such as arrest and conviction records compiled by police and court services (Moore, 2015). Such data can contain records of racially biased decision-making. Considering the case of arrest records, certain minorities, particularly Black people, are vulnerable to racially biased arrests in Western jurisdictions such as the UK (Shiner et al., 2018) and the US (e.g., Richardson et al., 2019) where risk assessment algorithms already influence sentencing decisions. As the technologies are designed to interpret historical arrest data as proxies for crime and objective risk predictors, they are likely to infer from the higher arrest rates of affected minorities that this group is more prone to criminality than others. This can prompt the tools to inflate their risk scores, reproducing biases embedded in the historical data (Hao and Stray, 2019; Mayson, 2019; Ugwudike, 2020). This also highlights the problem of lack of individualization involving predictions made on the basis of group risks rather than individual risk.

Risk predictions are only ever as good as the data on which the technologies rely: where the data comprises records of discriminatory decision-making, the predictions will reproduce the bias. If the predictions inform sentencing decision-making, principles of justice such as fairness and impartiality will be undermined.

Cultural bias

A related issue is that AI applications including risk assessment algorithms are not created in a normative or cultural vacuum. They reflect the westernized norms, values, and ideologies of their designers and procurers and can lack cultural relevance amongst non-Western communities. Indigenous groups in Australia and Canada where sentencing technologies are being deployed represent examples. In the case of Ewert v Canada Correctional Service (2018), for example, Jefferey Ewert, an indigenous Canadian was denied parole on the basis of high-risk predictions generated by risk assessment algorithms. On appeal, the Supreme Court of Canada agreed with Ewert that the technologies did not consider cultural factors relevant to indigenous communities and could instead label the factors as risky, exposing affected defendants to risk inflation. During sentencing, such risk amplification would undermine the principles of impartiality and fair treatment vital for the equitable administration of justice.

Socioeconomic bias

Bias based on adverse socioeconomic circumstances represents yet another challenge associated with the risk assessment algorithms that influence sentencing. As already noted, some of the commonly used risk assessment algorithms are designed to generate predictions based on predetermined risk factors selected by their designers. These include signs or indices of socioeconomic deprivation. Unsuitable or unstable accommodation, unemployment, poor educational attainment, and lack of engagement in lawful leisure activities are examples (Ministry of Justice, 2019). However, these can operate as proxies for deprivation, rendering socioeconomically disadvantaged defendants vulnerable to higher risk scores than they deserve (Van Eijk, 2016), which, again, undermines principles of justice.

Gender bias

Gender-related bias, which has also been associated with risk assessment algorithms, is another factor that poses implications for principles of justice, particularly procedural due process. Studies and commentators note that some of the tools have been trained and validated using data from young male populations, calling into question their suitability for women (e.g., van der Knaap et al., 2012). Concurrent work has also found that risk factors such as socioeconomic circumstances expose women to risk inflation as they tend to be more affected by inequalities in those areas compared with men and would as such appear riskier (Hamilton, 2019).

In sum, predetermined risk factors such as criminal history and socioeconomic status which inform algorithmic risk scores, can operate as proxies for race, gender, and socioeconomic status. In doing so, they introduce proscribed extrajudicial characteristics into sentencing decisions and undermine both procedural due process (see Article 6 of the UK's Human Rights Act 1998) and the right to non-discrimination (Article 14).

Transparency deficits

Lack of transparency represents yet another limitation associated with AI technologies in general (Oswald et al., 2022) including the risk assessment algorithms that inform sentencing decisions (Kehl et al., 2017). Given the level of advanced computational analysis involved, algorithms can evolve into black boxes. They can become esoteric or instructible even to their designers, who are in any event, protected by trade secret laws, meaning that they do not have to reveal the contents of their code. Even if sentencing technologies were transparent and open-source models, financial and technical resources for meaningful algorithm audit are still required. Such lack of transparency obfuscates conduits of bias and limits accountability. It also denies defendants the opportunity to rebut ascribed algorithmic risk scores, with adverse implications for the due process principle that is central to the fair administration of justice (see Article 6 of the Human Rights Act 1998; Ugwudike, 2020).

Relevance to criminology

The challenges presented by risk assessment algorithms used for sentencing fall within the purview of criminology, including the field of digital criminology, and the strand of the discipline that is concerned with social harms. Whilst challenges such as bias and lack of transparency are not proscribed by law, they produce serious social harms. Consider for instance, the potential implications of a high risk of recidivism score informed by racial, gender, or socioeconomic bias. It heightens the risk of an unwarranted custodial sentence which punishes the affected defendant for a future crime, denying them their civil rights and liberties. It also poses adverse consequences for their family (Ugwudike and Fleming, 2023). Post-release, their conviction undermines liberal principles of distributive justice; it unfairly restricts access to key resources, from accommodation and education to employment (see generally Corda et al., 2023).

Another area of criminological relevance is the capacity of risk assessment algorithms to undermine judicial autonomy. This can occur in two ways. One is via the expectation that judges should rely on decision-making tools commissioned by policymakers, blurring the constitutional boundary between the executive and judicial arms of government. Another is through the phenomenon of algorithm appreciation (Logg et al., 2019) or 'automation bias' (Goddard et al., 2012): algorithmic technologies extend the trend in sentencing that involves privileging data-driven, non-personalized, knowledge about defendants and imposing sentences based on similarities with a group rather than individual actions.

Conclusion and AI futures

The challenges of AI in sentencing compel us to reflect on how best to counteract them and design responsible models for the future. While some call for outright abolition (e. g., Schwerzmann, 2021), others pragmatically propose robust legal frameworks (e. g., Martini 2020). In the UK, official efforts to mitigate the challenges in the public sector include the introduction of an Algorithmic Transparency Standard which is an auditing system that has been trialled with the police (Oswald et al., 2022). Apart from audits, other technical remedies such as improving explainability (Zeng et al., 2015) and debiasing data have been proposed and trialled (Skeem and Lowenkamp, 2020). Some reject the very notion of debiased or unbiased data and argue quite persuasively that data always contains and reflects the choices, assumptions, and interpretations made during collection and processing (see Gitelman and Jackson, 2013; Ugwudike 2022). Remedial strategies must therefore focus on understanding the type of bias embedded in data and how best to mitigate them (Kaufmann, 2023).

Beyond technical mitigations, proffered structural remedies include equitable distribution of digital capital (van Dijk, 2005) in the form of access to technologies and design skills. At present, much of the digital capital required for constructing and auditing AI technologies resides in a few, centralizing power amongst them whilst excluding others who currently bear the culminative ethical burden of the technologies (Petrozzino, 2021; Ugwudike, 2022).

Main takeaways

- Risk assessment tools in the form of machine learning algorithms can directly influence sentencing decisions.
- Justifications offered for their use focus on assumptions of scientific objectivity, bias elimination, cost effectiveness, institutional efficiency, and public protection.
- Bias and lack of transparency are key challenges affecting the algorithms and they pose implications for justice.
- Proffered remedial strategies include legal and regulatory frameworks.
- Third-party audits have also been proposed to anticipate unintended consequences.
- Structural level remedies include access to digital capital to reverse the uneven distribution of risks and benefits.

Suggested reading

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