Coding Criminality: Sociotechnical Joint Optimization for Efficacy and Efficiency in the Criminal Justice System

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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The American criminal justice system is plagued by ineffective crime prevention (Alper et al., 2018; Kleck, 2014) and persistent racial and socioeconomic biases (Tonry, 2010; Kumer, 2023), hurting both criminals (Mueller-Smith, 2015) and the American public (Anderson, 2021). To target these issues, the justice system has enlisted the aid of several algorithms designed for this purpose. Many studies have analyzed the effectiveness of these algorithms and made arguments about their fairness and effectiveness (see, e.g., Blomberg et al., 2010; Freeman et al., 2021) but these studies have evaluated the algorithms more or less in isolation. This paper will analyze these algorithms through the lens of sociotechnical systems analysis to determine how the whole criminal justice system, including humans, algorithms, and their interactions, can best work together to advance the goals of the criminal justice system, including crime prevention and equal protection under the law. I will begin by outlining sociotechnical systems analysis and defining the relevant system boundaries, actors, and goals; then, using the implementation of the COMPAS Core Risk and Needs Assessment as a case study and drawing from my own experience working with data for the Albermarle-Charlottesville Regional Jail, I will outline how tasks can be better distributed to humans and algorithms to help solve some of the most pressing issues in the criminal justice system.

Sociotechnical systems analysis considers how the social (human) and technical (machine) subsystems of one hybrid system work together towards common goals, with the distribution of tasks between them optimized based on their respective strengths and needs (Imanghaliyeva et al., 2020). This optimization process is known as joint optimization, since it jointly considers both subsystems, the impact they will have on each other, and their relationship to society as a whole (Fox, 1995). In the criminal justice system, the social subsystem includes the police, the court system (including judges, juries, and clerks), jail and prison administrators, parole and probation agencies, and all supervisory boards (Kemp & Schwartz, 2022, p. 5). The technical subsystem would include all mechanisms, down to the locks on jail doors, but this paper will focus primarily on computer algorithms and databases, since the functions of these components overlap most with those of their human counterparts. Together, these subsystems work towards the mission of the criminal justice system: "to uphold the rule of law, to keep our country safe, and to protect civil rights" (U.S. Department of Justice, 2021, p. 4). This paper will focus on several tangible indicators of this mission: fair and equal treatment of U.S. citizens under the law as defined by the Equal Protection Clause of the U.S. Constitution, respect of human and civil rights, prevention and deterrence of future crime both by former criminals and would-be criminals, and a sense of safety and security for the American public, including the freedom to go about their daily activities without fear they or their property will come to harm.

Currently, the criminal justice system is falling short of this mission. While both property crime and violent crime rates have steadily fallen since the mid-1990s (Brennan Center, 2023), the failure of the criminal justice system to achieve its subgoals, including preventing recidivism (i.e., returns to custody) and treating all citizens equally, shows there is room for improvement. To start, the "tough on crime" punitive justice model deployed in the 1980s is still used widely, despite evidence demonstrating its inefficacy. Mass incarceration traps people, especially poorer people and minorities, in cycles of unemployment, crime, and rearrest. For each additional year an inmate spends in prison, their post-incarceration unemployment likelihood rises 3.6 percentage points (Mueller-Smith, 2015, p. 28). In part because of this, longer sentences increase the likelihood former criminals will return to prison (Song, 1993, p. 6); 68% of former criminals are rearrested within 3 years of their release and 83% are rearrested within 9 years (Alper et al., 2018). This shows a failure to adequately address the issues that led incarcerated persons to commit a crime in the first place. Instead, incarceration destabilizes lives: disconnected from their support networks, income source, and housing, formerly incarcerated people struggle to get back on their feet and live stable, law-abiding lives.

This is a devastating impact to wreak on so much of America's population - 6.6% of Americans will be incarcerated at some point in their lives, including a staggering 32.2% of Black men (Bonczer, 2003) - but it may be worth it if these incarcerations deterred others from committing crimes that would cause them to be incarcerated. However, no evidence has been able to demonstrate such an impact. Several states rolled out "Scared Straight" programs where "high-risk" youths were brought to prisons to meet inmates, on the theory that they would be scared out of committing a future crime. In each case, youths in the program were either equally likely or more likely to commit a crime than their similarly "high-risk" peers who were not put through the program (Petrosino et al., 2003), demonstrating the inefficacy of deterrence based on fear of incarceration alone. Most people committing crimes assume they will enjoy the benefits of their crime and won't be caught, negating the fear impact of deterrence (Kleck, 2014). Because the current punitive justice model is proven to increase, rather than decrease, crime through its use of mass incarceration, it undermines the criminal justice system's aims of upholding the rule of law.

Another stumbling block between the criminal justice system and its goals is systemic racism and socioeconomic bias. Incarceration rates for Black Americans average five to seven times higher than those of white Americans (Tonry, 2010). In particular, Black people are far more likely to be arrested for and incarcerated for misdemeanors than white Americans (Tonry, 2010). This violates their civil right to equal protection under the law, going against the mission of the criminal justice system. Even innocent people of color face higher rates of harassment by law enforcement than white Americans (Carvalho et al., 2021), which undermines their sense of security and trust in police (Fratello et al., 2023), counter to the justice system's mission. Beyond this, poorer people face higher incarceration rates. Albemarle-Charlottesville Regional Jail (ACRJ) Superintendent Martin Kumer, reflecting on his jail's population, stated: "There is one thing everyone here has in common. They are all poor." (Kumer, 2023). A myriad of misdemeanors criminalize aspects of life under the poverty line, including petty theft, substance abuse, and vagrancy (homelessness). In contrast, white-collar crime is significantly under-investigated and under-caught (O'Neil, 2017, p. 84), and wealthier people who are arrested are able to afford bail and lawyers who can reduce their prison time - an even more important advantage given the detrimental effects of incarceration outlined above. The unequal treatment of people in the criminal justice system on the basis of race and wealth goes against the criminal justice system's mission of equal protection under the law.

To complete the process of joint optimization, it is important to first define the strengths and weaknesses of the social and technical subsystems. Finding a lack of sources on this, especially for humans and algorithms in the criminal justice system, I will draw from my own experiences creating and working with these algorithms as a systems engineer (see Banino et al., 2024) to outline these strengths. Algorithms are very good at finding patterns in data and perpetuating them, which is great if the dataset is one you want to perpetuate exactly, but not great if that dataset is biased in any way, as many, if not all, of the datasets in the criminal justice system are (Freeman et al., 2021). They are also very good at data management, including data collection, storage, analysis, and communication. Humans, on the other hand, are better at solving novel problems than algorithms (Harari, 2019): when we encounter a unique situation, we are better equipped to pull in relevant information and solve it creatively. Humans are also stronger than algorithms in our ability to consider the ethics of the data and patterns we're utilizing. And, because of our compassion, humans can connect better with other humans than an algorithm can.

Several companies have developed algorithms to help criminal justice organizations more effectively rehabilitate inmates and eliminate bias, including deciding patrol areas, automating elements of sentencing, and developing treatment plans, all of which have been implemented across the country. For this paper, I will take one of the most popular as a representative case study: the COMPAS Core Risk and Needs Assessment (CoreRNA), developed by Northpointe, Inc. This algorithm is based on the risk-needs-responsivity (RNR) model, which, contrary to the punitive justice model, argues that rehabilitation can best be achieved by focusing treatment on inmates at a higher risk of recidivism and tailoring their treatment plan to their criminogenic factors (i.e., the characteristics that put that inmate at risk for committing another crime) (Ward et al., 2007). This algorithm uses dozens of data points collected from the defendant or inmate, combined with weights determined by machine learning, to score their risk of being rearrested (1 being low-risk and 6 being high-risk), relative to the rest of that agency's population (Northpointe Inc., 2019). The algorithm uses the same information to score people on twenty-two needs scales covering criminogenic factors from substance abuse to criminal personality (Northpointe Inc., 2019). The risk scores dictate how intense their treatment program should be - if they're at a higher risk of recidivating, RNR states they should receive more resources, while if they're at a lower risk of recidivating, they should be kept away from the more hardened criminals. The risk scores can also be used to allocate scarce resources. The needs scores dictate what form their treatment should take, with options including classes, job training, and drug rehabilitation. Together, the risk and needs scores are intended to be used to create a treatment plan tailored to each inmate in type and intensity.

While the intentions were good, the CoreRNA is an excellent example of failed joint optimization, filling roles that humans are better at. The first of these is analyzing inmates' backgrounds to determine the type and intensity of their treatment. Each inmate can be considered as a novel problem, with unique experiences that affect what treatment would work best for them. As such, they are best solved by humans, who are better suited for novel problems because we can solve problems creatively and bring in new information as it becomes relevant. Algorithms can only consider the information they are told to consider ahead of time. While the CoreRNA does consider many important criminogenic factors, it cannot ask follow-up questions or piece together how factors may relate to each other. A human caseworker, talking with an inmate, can dive deeper and bring in external information as appropriate. For example, the scores may flag an inmate for antisocial attitudes, but miss that these attitudes are the result of a specific trauma they experienced. Based on this score, the algorithm would recommend helpful social classes, but wouldn't know to recommend therapy to heal that trauma. Algorithms also cannot consider the broader context of their findings and weigh them against external factors. For example, the risk score may be able to find the quantitative variables that correlate most with recidivism, but the algorithm cannot thoughtfully weigh this risk with other important factors that may affect efficient resource allocation. For example, studies show that having parents who spent time in prison increases one's own risk of committing a crime (Rowe and Farrington, 2006), so it may be worth investing more resources in stabilizing a parent in order to prevent their children from committing crimes. Only a human caseworker can balance these considerations with compassion and nuance.

This lack of compassion and nuance also harms algorithms' ability to connect with inmates, establish trust, and boost engagement in recidivism-prevention programs. According to Lisa Hensley, a caseworker at ACRJ, many inmates, during the CoreRNA data collection interview, downplay their criminogenic factors to avoid having to go through programs to correct them. Having a freeform, human-to-human conversation about these criminogenic factors may help inmates understand why addressing these factors could help stabilize their lives, and thus increase their commitment to the program. An algorithm could not walk inmates through this in the same way. Humans can also have a back-and-forth conversation with inmates, responding to their questions and concerns and tailoring the program accordingly if need be. This responsivity allows inmates to add information vital to the treatment plan, understand why they are receiving a certain treatment plan, and feel like they have had a part in creating it, which would encourage engagement. Lastly, the rigid scores algorithms output may hurt inmate engagement with their treatment. If inmates are told they are "high risk," this label may become what psychologists refer to as a self-fulfilling prophecy: they may internalize this label and modify their behavior to match it. They may limit their own potential, believing they are doomed to recidivate, causing them to engage less with classes and treatments designed to prevent recidivism and instead revert to old, criminal habits when they are released. Humans can better connect with our fellow humans, which would be helpful psychologically as well as practically.

However, while humans are better equipped to connect emotionally with inmates and consider broad information to develop a novel treatment plan, algorithms can still contribute to the goal of recidivism prevention with their primary strength: processing large amounts of information and presenting key takeaways. An algorithm could generate a dossier on the inmate's criminal history, recommendations for treatments that have helped similar inmates, and example questions to ask, allowing the human caseworker to prepare for the conversation, consider possible treatment tools, and fact-check the inmate when necessary. This informs the conversation beyond the scope of human knowledge without taking over the responsibility of compassion and creative problem-solving that is best left to humans. The key difference between this role and the one assumed by COMPAS is who is in the driver's seat. When there's just a scalar score, it's all too simple to defer to the algorithm: across fields, human experts defer to algorithms even when it goes against their experience and judgment, due to the perceived accuracy, neutrality, and evidence basis of algorithms (Cabitza et al., 2017; Seyyed-Kalantari et al., 2021). In addition, in the criminal justice system, officials are often overburdened (Kumer, 2023), and thus reliance on algorithms' simple scores can be an easy crutch. For decision-making in the criminal justice system to be optimal, algorithms should increase the amount of information available to decision-makers, rather than decrease it, and humans should remain firmly in control of the decision-making process.

The COMPAS CoreRNA has also been used to tackle the problem of bias in the criminal justice system, a task that it is similarly ill-equipped to confront. As stated earlier, minorities face harsher sentences due to the implicit bias of judges. To reduce this bias, some courts have begun using defendants' risk scores from the CoreRNA to determine their prison sentence lengths, with higher-risk inmates receiving longer sentences, on the theory that this increases neutrality. From an ethical perspective, this practice is problematic because it effectively punishes defendants for crimes they haven't committed yet that an algorithm believes they are likely to commit. The algorithm has come to this conclusion based on the criminal histories of defendants from similar backgrounds and demographics; so, defendants are receiving longer sentences because people of the same demographic as them are arrested more often.

This is troubling on its own and violates defendants' rights under the Equal Protection Clause (Starr, 2014), but it's even more troubling given the disproportionate arrest and incarceration of Black people. The CoreRNA uses arrest events as a proxy for committing crimes (Northpointe, Inc., 2019), but Black people are more likely to be arrested regardless of innocence status (Tonry, 2010). Therefore, the CoreRNA scores will be racially biased because it was trained on a dataset that is racially biased (Freeman et al., 2021). Even if the CoreRNA used convictions as its proxy, the result would still be biased because with higher arrest rates, Black people are more likely to be caught for minor crimes, and judges are also less likely to give them the benefit of the doubt (Tonry, 2010). All the statistical methods can be valid and still result in a biased outcome because of the history of over-incarceration of Black people in America. Any algorithm trained on this data, including similarly popular predictive policing models that dictate areas to patrol more heavily, would likely have the same issue, since this pattern perpetuation is a central characteristic of machine-learning algorithms. Therefore, because algorithms in this role violate the system's goal of fair and equal treatment of all citizens, humans, rather than algorithms, should occupy this role in the system.

While humans can be, and often are, guilty of similar biases, we have key advantages over their algorithmic counterparts. While racism and other biases, especially implicit and systemic biases, are still very present in the criminal justice system, this presence has decreased over the past few decades, such that the aggregate human in the justice system today is less biased than the aggregate human a decade or two ago. Misdemeanor arrests, which are disproportionately aimed at minorities, have decreased in the past thirty years (Beck and Holder, 2022). Disparities between races in conviction and sentencing, while still very present, have decreased somewhat over time, according to a study of Connecticut juvenile prosecution (Zane, 2021). This matters because algorithms that generate predictions are based on data from past arrests and convictions, so they are based on the decisions of past human decision-makers. Since the past average human decision-maker is more biased than the current average human decision-maker, the average decisions of algorithms will be more biased than those of current humans. While it is possible to adjust algorithms to moderately reduce bias (Skeem and Lowenkamp, 2020), algorithms' reliance on biased datasets makes it difficult, if not impossible, for them to fully divorce their decisions from those of biased past human decision-makers. However, algorithms can be used to reduce the bias of human decision makers in a different way. Algorithms are great at sorting through large amounts of data and providing regular updates on pre-coded questions. This strength can be utilized to generate reports on a regular basis regarding the racial makeup of judicial decisions at several points of the justice process, allowing the public to better hold the justice system accountable to its goals of equity, using the information output by algorithms. Though there is no simple solution to reduce biased decision-making in the criminal justice system, properly distributing tasks towards this end can help.

Beyond this automated research, algorithms could assist humans who are conducting novel research by cleaning, collecting, and presenting information. A large, centralized database of criminal justice data would enable human researchers to ask new questions regarding the criminal justice system, bringing about positive policy change. Currently, this large database does not exist: individual agencies set their own data management practices with varying amounts of input from other agencies, making it difficult to compare data across jurisdictions (Itswany, 2023). The data that is collected is riddled with human errors, including typos (Itswany, 2023, and my own research for Banino et al., 2024); though humans have many strengths, consistent precision is not one of them. The data collected is not well shared between agencies, partly due to different data practices and partly due to privacy concerns. While this data is usually sufficient for day-to-day operations, the limitations interfere with attempts to learn from this data. For example, the State of Virginia was studying outcomes based on past criminal history, but it could only consider criminal history from within the state (Virginia Criminal Sentencing Commission, 2023). Considering the average American will move states twice during their lifetime (U.S. Census Bureau, 2023; Xu et al., 2022), this is a significant limitation for research. It would also limit the usefulness of dossiers, since criminal history from outside the state could not be used with the current restrictions.

Algorithms could help organize this database. Algorithms are great at identifying deviations from clear rules, and thus could identify many errors in data entry. For example, an algorithm could match addresses to the postal database and flag entries that don't appear to exist. An algorithm could also analyze scans of inmates' driver's licenses to automatically upload some of the inmates' basic information, reducing room for human error during data entry and speeding up the booking process. However, for data to be comparable across agencies and jurisdictions, governments would need to create higher-level guidelines for what information agencies should collect and lift current restrictions on sharing data between states. Algorithms already encrypt this data to minimize privacy concerns, and these protections can be increased. This combination of algorithmic and human organization is necessary to create a database optimized for serving the goals of the criminal justice system through information provision.

Joint optimization, as outlined by sociotechnical systems analysis, can help the criminal justice system increase its efficacy and equity by optimizing the performance of human and algorithmic actors. Future research should explore further areas where tasks should be transferred from humans to algorithms and vice versa. In particular, there are many tasks currently performed by humans for which algorithms are not typically used and may not even exist, but could be very useful. Examples include the detection of financial fraud and similar white-collar crimes in financial records and tax returns (a very detail-oriented task with clear rules) and preliminary paperwork processing (also detail-oriented, also clear rules). Both of these applications could free up humans to do more creative work, including the treatment plan development described above, while increasing the number of crimes and errors caught. In general, algorithms can best aid the criminal justice system's goals by making more easily digestible information available to humans. This approach is conscious of humans' and algorithms' respective strengths and weaknesses: humans are limited, especially in knowledge, but properly used algorithms could extend human capacity by presenting them with information and providing mechanisms for accountability. In this way, humans and algorithms can work together to create a more just society.

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