

Courts and Predictive Algorithms

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Introduction¹

Classical descriptions of courts and trials usually emphasize the dignity, slow pace, and time-honored legal expertise of the judges and prosecutors in charge of criminal cases. Courts are seldom described as sites where data analytics and algorithms flourish. Yet one of the most striking innovations of the criminal justice system during the past thirty years has been the introduction of statistical models and software programs designed to help judges, prosecutors, and other court staff assess the “risk” of criminal offenders.

While the use of statistical techniques in criminal justice is not new,² the number and sophistication of these algorithms has vastly increased over the past decades. The term ‘algorithm’ comes from computer science, rather than law, and refers to an automatic rule that uses numerical inputs to produce some result, in this case a prediction relevant to the criminal justice system. In practice, it refers to the automation of a statistical method. Over the past thirty years, statistical methods originally designed for use in probation and parole decisions have become more advanced and more widely adopted, not only for probation and bail decisions, but also for sentencing itself.³ Based on a small number of variables about defendants, either connected to their criminal history (previous offenses, failure to appear in court, violent offenses, etc.) or socio-demographic characteristics (age, sex, employment status, drug history, etc.), such algorithms typically provide an estimate of an offender’s risk of recidivism or risk of failing to appear when on bail, from “low” to “high.”

Advocates for statistical approaches to criminal justice highlight the many benefits associated with risk-assessment tools. In their view, predictive algorithms rationalize the decision-making process by summarizing all relevant information in a more efficient way than the human brain: for instance, that actuarial assessments would do a better job than individualized judgment at predicting risk and therefore would help strike a better balance between reducing incarceration and promoting public safety.⁴ Advocates also hope that risk-assessment tools will help curb a history of racism and discrimination embedded in the U.S. criminal justice system by reducing

disparities in the interpretation of the information available to judges, prosecutors, and other court staff when they make decisions.⁵ Data-driven initiatives are frequently said to minimize incarceration rates and the length of imprisonment for low-risk offenders, resulting in lower budgetary costs and reduced social harm.⁶

Using predictive algorithms may also save precious time for overworked prosecutors, judges, clerks, and other court staff.⁷ Yet there is still very limited empirical research about whether predictive algorithms accomplish all of these goals.

Evidence-based initiatives attract significant political bipartisan support and are popular among practitioners, non-profits, and governmental institutions. For instance, the American Law Institute recommends a broader use of risk-assessment tools in the most recent version of their highly influential Model Penal Code.⁸ Yet, scholars imply that as a management stratagem, risk-assessment tools move judicial scrutiny away from public review and towards proprietary methods by private industry actors.⁹ These tools may impact how judges, prosecutors, and court staff exert their own discretion, even if they don't perceive a difference, and the outcomes of risk assessment algorithms may be skewed due to the use of socio-economic variables, biases in the data, and inaccurate predictions.

Increased reliance on predictive algorithms takes place within a broader context of mass incarceration and racial discrimination in the U.S. criminal justice system. The United States, which represents 5% of the world population, has 25% of the world's prisoners: 2.2 million people (including pretrial detainees) are currently incarcerated.¹⁰ According to the most recent figures, 1 in 12 black men between 25 and 56 years old is currently in jail.¹¹ Racial discrimination takes place at every step of the criminal justice system, from policing to bail, plea, sentencing, probation, and parole. Part of what is driving the introduction of algorithms in courts is the hope that these new tools will have a positive impact on the overall fairness of the system.¹² Examining the concrete practices associated with the uses of predictive algorithms in courts is crucial to assessing the efficacy of this agenda.

The primer examines four questions:

1. How are predictive algorithms constructed?
2. How do judges and prosecutors use the algorithms?
3. How does evidence-based sentencing affect disempowered groups and the criminal justice system as a whole?
4. What kind of data is missing?

Predictive algorithms in the U.S. criminal justice system

There are four major areas of the criminal justice system where predictive algorithms are now used:

1. Pretrial and bail

Over the past forty years, about 10% of courts have developed their own risk-assessment tools.¹³ In 2015, the Arnold Foundation launched a new instrument, the “Public Safety Assessment-Court” (PSA), which relies on several variables related to the age of the defendant and his or her criminal record and previous failures to appear in court in order to “accurately, quickly, and efficiently assess the risk that a defendant will engage in violence, commit a crime, or fail to come back to court.” The PSA is currently used by 21 jurisdictions, including three entire states (Arizona, Kentucky, and New Jersey) and three major cities (Charlotte, Chicago, and Phoenix). According to the Arnold Foundation, it has led to lower crime rates and a decrease in jail population in the jurisdictions where it was used.¹⁴

2. Criminal sentencing

In 1984, the Sentencing Reform Act led to the creation of the U.S. Sentencing Commission and the Sentencing Tables, a mandatory federal instrument imposing determinate ranges of incarceration time for serious federal crimes. Under federal law, the Sentencing Tables reflected a mixture of goals, including “the need for the sentence imposed...to provide just punishment for the offense and at the same time to protect the public from further crimes of the defendant.”¹⁵ The columns categorize the criminal history of the defendant, while the rows describe her offense level, and each box provides a range of the length of incarceration (for example, 10-16 months of imprisonment).¹⁶ The Sentencing Tables became advisory (not mandatory, but still significant) in 2005. Many other risk-assessment instruments have emerged since then, some of which go beyond the Sentencing Tables to consider factors not directly connected to the crime (such as the socio-demographic characteristics of the defendant). For instance, Pennsylvania’s Sentencing Commission has been developing a risk assessment scale to determine what level of recidivism risk is associated with all adult defendants and recently published a report suggesting it may use age, gender, and the defendant’s place of residence as determining factors under the new guidelines.¹⁷

3. Probation and Parole

The number of states using a risk-assessment tool for parole decisions increased from 1 in 1979 to 23 in 2004.¹⁸ Two highly popular prediction instruments are the LSI-R (Level of Services Inventory-Revised), a proprietary product of the private company Multi-Health Systems¹⁹ and COMPAS (Correctional Offender Management Profiling for Alternative Sanctions), a proprietary product of Northpointe, Inc.²⁰ As noted by law professor Sonja B. Starr, “the LSI-R includes not just the defendant’s current living situation but also history variables outside the defendant’s control; for instance, a defendant will be considered higher risk if his parents had criminal backgrounds.”²¹ Instruments such as LSI-R and COMPAS are used for many purposes, including

the security classification of prison inmates but also their eligibility for parole and levels of probation and parole supervision.

4. Juvenile Justice

Since 1993, the Annie E. Casey Foundation has been developing a “Risk Assessment Instrument” (RAI), which was implemented in 2014 in more than 300 jurisdictions across 39 states. The RAI score indicates “whether the child is eligible for secure detention, for a non-secure detention alternative program, or for release home” (both before and after the trial). According to the Casey Foundation, there has been a 46% drop in the detention of youths of color after the instrument was adopted, though several causes might be responsible for this change, including the adoption of other reforms designed to make the system less incarceration-oriented.²² A similar initiative is currently taking place in Florida, where the Department of Juvenile Justice collaborated with a company called Algorhythm to build a predictive tool for juvenile offenders.²³

Constructing the algorithms: different actors, varying methods

A wide and heterogeneous range of actors contributes to the construction and implementation of algorithmic approaches to criminal justice in the United States, including governmental organizations – both federal and local – as well as non-profit organizations and private corporations. All of these actors have different resources for contributing to the analysis. Technology developers make different choices about the data sets, computing skills, and testing methods used to build the predictive instruments. Such choices in turn shape the variables taken into account in the models, which can vary widely, and affect the results provided by the risk-assessment tools.

How is a risk-assessment algorithm built? Statisticians create predictive models by “training” computers with large sets of historical data. By taking the records of past criminal cases – including data on sentences, recidivism, and demographics – a statistician can identify which variables show up the most in relevant cases. Then, statisticians reverse the process, looking for those same variables in new cases in order to make predictions. If their predictions achieve a sufficient level of accuracy in controlled tests, the algorithm can be deemed predictive and applied to active cases. As in all other types of statistical analysis, dealing with a small sample size or a large amount of missing data (e.g., incomplete records for which variables such as the defendant’s prior criminal record, perhaps occurring in another jurisdiction, is lacking) is a challenge because it can make the model less accurate. Statisticians and computer scientists also need to decide which modeling strategy to adopt. These models may be created manually using basic statistical techniques. Or, an algorithm can generate the model specific to the given data through machine learning techniques.²⁴ An overwhelming majority of existing risk-assessment tools rely on more basic strategies and static models. Statisticians then reverse the model: instead of examining the causes of recidivism, the model is used to predict the risk of recidivism for any given individual.

Last, the algorithm is tested and its predictions are compared to actual cases that have been sentenced by judges, either in the past (“retrospective sampling”) or based on new referrals received during a given period of time after the development of the algorithm (“prospective sampling”).²⁵

Depending on the financial means of the organization constructing the algorithm and the size of the jurisdiction concerned, the size of the data set, the amount of missing data, and the sophistication of the modeling techniques used, the quality of the algorithm will vary. For example, the Arnold Foundation’s PSA pretrial instrument uses a database of over 1.5 million cases from 300 jurisdictions. Other instruments rely on data as small as several thousand cases. In some cases, the algorithm is even built using what is called the “consensus method,” that is, without a data set or statistical test. Rather, judges and criminal justice specialists agree on a set of variables that, in their opinion, are significant in estimating the risk of an offender.²⁶

These differences in resources and methods lead to a wide range of variation between the algorithms. For example, whereas the Arnold Foundation’s PSA only considers variables having to do with the criminal history of the defendant and her age, most pretrial risk assessment tools, including the one used in Virginia, includes additional variables such as employment situation, length at residence, whether the offender is a primary caregiver, and whether she has a history of drug abuse.²⁷ Other risk-assessment tools include a quick psychological survey and take into account “subjective” variables about the defendant’s “emotional status” or “personal attitude,” even though psychologists rarely administer the surveys.²⁸

Algorithms, fairness, and disparities

This proliferation and piecemeal adoption of predictive algorithms developed using a wide range of methods raises significant questions about the fairness of the judicial system as a whole, particularly when such tools move outside of probation and parole decisions into sentencing. The U.S. legal system provides officials with substantial discretion over parole and probation – discretion that has been used to implement predictive, statistical techniques – but there are still significant legal protections at the sentencing stage.

Following former Attorney General Eric H. Holder’s worries about “unwarranted sentencing disparities” between jurisdictions and his recent reminder that the current system runs the risk of deviating from “the principle that offenders who commit similar offenses and have comparable criminal histories should be sentenced similarly,”²⁹ it is important to consider whether or not the trend toward using risk assessment tools at the sentencing stage might increase or decrease sentencing disparities within and between jurisdictions. Will wealthier jurisdictions have more sophisticated predictive instruments than poorer jurisdictions? Will it make a significant difference for defendants to be sentenced in one jurisdiction rather than another because one or the other has a “friendlier” algorithm? Although these algorithms are not making judgments in lieu of

judges, it is not yet clear how these judges are incorporating them into their process, how the algorithm influences their decisions, or how these new tools challenge or reinforce pre-existing biases and inequities in judicial decision-making.

Regardless of their impact, the very method used to build these algorithms might make them unconstitutional. None of the sentencing instruments use race as a variable, yet many variables included in the models play the role of ‘proxies’ for race, in that they strongly correlate with race and reflect racial bias. For example, considering a defendant’s place of residence (e.g. zip codes) can end up targeting neighborhoods where residents are predominantly low-income African-Americans. These group-based features are then incorporated into the algorithms, which may mean that racial minorities face longer sentences for the same crimes as similarly adjudicated non-minority defendants. This goes further than race. For example, many risk-assessment tools take gender into account in their algorithm, since men are statistically more likely to commit offenses than women.

Starr argues that statistical sentencing based on gender and socio-economic characteristics is unconstitutional. As Starr explains, “the Supreme Court has squarely rejected statistical discrimination – use of group tendencies as a proxy for individual characteristics – as permissible justification for otherwise constitutionally forbidden discrimination.”³⁰ People have the right to be treated – and sentenced – as individuals and not on account of “risky” characteristics of a group to which they belong. The ACLU challenged the constitutionality of risk-assessment tools along similar lines and filed an amicus brief in the Virginia Court of Appeals, arguing that sentencing based on statistical generalizations “cuts to the core of the fundamental constitutional principles of equality and fairness.”³¹ Several practitioners have disagreed with these positions, however, and maintained their support for risk-assessment tools that do not include socio-economic variables in the models.³²

Most analyses of this question still suffer from a lack of information. Risk-assessment algorithms are usually kept secret and proprietary: most actors (non-profit companies, for-profit companies, and jurisdictions) refuse to share either the algorithms or the training data sets.

Using algorithms in the criminal justice system: shifting discretion

How are sentencing algorithms used in courthouses? The daily practices associated with data-driven sentencing might not always match the ambitious goals of the advocates who started the process. In fact, an increased reliance on risk-assessment tools might come with unintended effects.

Take the example of discretion: one of the main arguments developed by advocates of data-driven sentencing is that algorithms should be favored because they reduce discretion, not in a direct way

but by “nudging” judges, prosecutors, and other court staff to follow the predictions of the algorithm.³³ These advocates argue that quantification helps to hold judges and prosecutors more accountable for their decisions. Algorithms and “smart statistics” are presented as an easy solution for making sentencing more consistent and efficient.³⁴ But little is known about the efficacy of such interventions.

Historical examples can be introduced as cautionary tales. Consider the dynamics surrounding Sentencing Guidelines, a process intended to address earlier concerns about discretion. Beginning in the mid-1960s, a broad bipartisan movement emerged to promote sentencing reform. Progressive advocates thought that existing disparities in sentencing revealed overt discrimination and a punitive mindset among judges, whereas right-wing groups believed that judges were too lenient and saw them as the primary culprits for rising crime rates. Both groups thought that determinate sentencing was the solution. They supported the Sentencing Reform Act and the creation of Sentencing Guidelines, which were sponsored by Senator Ted Kennedy and passed in 1984.³⁵

It soon turned out that instead of eliminating discretion, the Sentencing Guidelines led to a displacement of discretion. Judges started complaining about the Guidelines, which they found constraining and complicated to use. The Guidelines kept changing to take into account new categories of offenses, a more complex system of exceptions and reductions emerged over time, and judges struggled to follow and implement these changes.

Prosecutors, however, were not constrained at all by the Guidelines. They saw instead a significant increase in their relative decision-making power: they were the ones deciding on the charges that would then constrain the decision of the judges, since it would determine the “Offense Level” column in the Sentencing Tables. In addition, the increasing number of criminal cases and general overload of the court system led to a dramatic increase in plea-bargaining, a mechanism where prosecutorial discretion rather than judicial discretion reigns. Today, 97% of cases do not go to trial: they end in a plea bargain with a prosecutor.³⁶

In other words, discretion did not disappear with the Sentencing Guidelines. Instead, it shifted from judges to prosecutors. The Guidelines became advisory instead of mandatory in 2005, but their effects are here to stay; the exponential increase in plea bargaining is widely believed to have contributed to increasing rates and lengths of incarceration sentences for low-income minorities.³⁷

Learning from the case of the Sentencing Guidelines, we need to ask similar questions about the rise of algorithmic sentencing. Instead of assuming that risk-assessment tools will rationalize the decision-making process, make judges and prosecutors more accountable, and curb discrimination, we should pay more attention to the unintended shifts of discretion that they might entail. Who will be responsible for entering the names and characteristics of the defendants into the software program? Who will be reading and interpreting the results? What practices will

become common-place as people exploit or optimize for algorithmic results? And how will these displace or shift sentencing practices and power in ways that parallel the shifts in power and discretion that resulted from the introduction of the Sentencing Guidelines? Which strategies will people be able to develop in order to change the settings of the software program when a result does not match their intuition? Examining such practical questions is crucial in order to understand the actual effects of evidence- based instruments on criminal sentencing.

“Overrides,” incarceration, and the role of punishment

A final major question emerges in examining risk-assessment tools: how can we assess whether algorithms contribute to lower rates of incarceration and improve the fairness of the criminal justice system instead of worsen it?

Advocates of risk-based sentencing argue that in their current form algorithms merely provide ‘indicative’ predictions of risk. Most judges and prosecutors also argue that they do not blindly follow the results provided by algorithms when making a decision about an individual offender: they rely on their expertise and clinical experience to assess her personality, situation, and risk of recidivism.

Yet existing research in behavioral economics and cognitive sociology shows that it is psychologically difficult and rare to “override” the recommendations provided by an algorithm.³⁸ In fact, judges and prosecutors are likely to follow the predictions provided by risk-assessment tools. A quantitative assessment provided by a software program generally seems more reliable, scientific, and legitimate than other sources of information, including one’s feelings about an offender. This is the case not only for laymen, but also for highly trained professionals³⁹: it is hard to challenge numbers and equations when one has not been trained in statistics. Consequently, when the algorithm provides a “high” estimate of risk, the tendency will be to incarcerate, regardless of other factors. Judges and prosecutors might also override the algorithmic information in biased ways. A recent report on juvenile justice shows that “detain overrides” (e.g., a judge’s decision to incarcerate a defendant when the algorithm provides a low risk estimate) are much more frequent than “release overrides” (e.g., the decision to release a defendant when the algorithm provides a high risk estimate).⁴⁰

Eventually, judges and prosecutors might change their sentencing practices in order to match the predictions of the algorithms. As behavioral economists Amos Tversky and Daniel Kahneman have shown, “anchoring” plays an important role in decision-making: people draw on the very first piece of evidence at their disposal, however weak, when making subsequent decisions.⁴¹ If the predictions of the algorithms are higher than the ones that judges had in mind, they might increase their sentences without realizing that they are following the algorithm. Professional training should act against anchoring, yet judges and prosecutors might not be entirely immune.

Perhaps even more problematic is the theory of justice implicitly embedded in the algorithms. Punishment is usually said to have four main justifications: retribution (the punishment must fit the crime and be proportionate to the severity of the infraction), deterrence (the punishment discourages people from committing crimes), incapacitation (the punishment positively prevents someone from offending, for example through imprisonment), and rehabilitation (which emphasizes instead the potential recovery of offenders and their inclusion in the social body). Risk-assessment tools emphasize one major justification at the detriment of the others: incapacitation.⁴² As currently designed, algorithms privilege a view of justice based on estimating the “risk” posed by the offender when deciding on a sentence designed to incapacitate dangerous individuals. Considerations of retribution, deterrence, and rehabilitation are not embedded in the current versions of these algorithms.

Although intended to do the opposite, there is a risk that risk-assessment tools may augur for even more incarceration than the methods they replace, going against the goal of many advocates on the left who support evidence-based reform in the hopes that it will reduce incarceration. This poses a set of important questions on the best way to encourage judges and prosecutors to use algorithms for lowering rather than increasing sentences. What could be changed in the design of the software programs to make judges and prosecutors more likely to override the predictions when needed?⁴³ How could we include non-incapacitative goals in the statistical tools? These questions need to be raised before sentencing algorithms become completely institutionalized in their current form.

Where data is needed

Several broader issues make it hard to assess and reform the decision-making process in criminal justice. One of them is the lack of data comparing the sentencing decisions of different judges, courts, jurisdictions, and states. In response to long-standing concerns and growing public debate on the fairness and efficacy of the criminal justice system, there has been a steady increase in tools, like software programs, that can provide performance indicators about decision-making practices in criminal justice.⁴⁴

Yet we also need more information about the content of sentencing decisions. How do rates of incarceration vary depending on the prosecutor, judges, court, and state involved? Similarly, how do these change depending on where one looks in the criminal justice chain (policing, bail, sentencing, probation and parole)? Judges and prosecutors might welcome this feedback about their decisions: many judges explain that they suffer from isolation and do not know how their decisions compare to the ones of their colleagues; they are often shocked when they find out that there are significant differences.⁴⁵

Several organizations are securing reliable evidence about sentencing decisions across jurisdictions,⁴⁶ but more work remains to be done. Risk-assessment-tools could aid in this process.

For example, in addition to predicting risk and providing recommendations about sentencing, algorithms could compare the actual decisions of the judges and prosecutors who used them and compile comparative statistics at the level of the jurisdiction. This type of feedback, analyzed and interpreted by different actors invested in improving criminal justice might make a significant difference in changing the current system.

Questions

1. What role should algorithms play in criminal justice decision-making? How can we make certain that these tools are not used inappropriately?
2. Are data-driven parole, probation, bail, and sentencing risk-assessment tools used to correct biases in the criminal justice system and reduce high rates of incarceration? There is limited empirical research on the efficacy of risk-assessment algorithms in producing more fair outcomes. How can we make sure that the rhetoric of putting an end to mass incarceration is not retooled to justify adopting tools that have little to do with this goal?
3. How can we train judges and prosecutors to use the algorithms in ways that will reduce discrimination and mass incarceration? What should be the role of law schools in this process?
4. What types of variables should be included in the algorithms? How can we make sure that the variables do not increase inequality between groups instead of reducing it? Are tools using variables about the socio-economic background and gender of the defendant unconstitutional? If so, what are the consequences?
5. How could we make sentencing algorithms and risk-assessment tools accessible? What about sharing the data sets used to calibrate data scores? What processes should be in place to build trust around the algorithms themselves?
6. How can we avoid a situation in which algorithms become “black boxes” that cannot be fixed? Who has the power to change an algorithm? How do we ensure algorithmic accountability? Can we imagine a system with regular checks by a third-party agency? What about the defendants themselves and their attorneys: could they have access to the algorithms used to estimate their level of “risk”? How do they challenge and interrogate proprietary tools?

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⁸ Starr, Sonja B. 2014. "Evidence-Based Sentencing and the Scientific Rationalization of Discrimination." *Stanford Law Review* 66 (4): 803-871, here p. 815-816. <https://www.stanfordlawreview.org/sites/default/files/66StanLRev803-Starr.pdf>.

⁹ For legal scholarship on the topic, see Garland, David. 2002. *The Culture of Control: Crime and Social Order in Contemporary Society*. Chicago: University Of Chicago Press.

¹⁰ "Criminal Justice Fact Sheet," NAACP, Accessed October 19, 2015. <http://www.naacp.org/pages/criminal-justice-fact-sheet>; "World Prison Brief: United States of America," *Institute for Criminal Policy Research*, <http://www.prisonstudies.org/country/united-states-america>; Lee, Michelle Ye Hee. "Does the United States Really Have 5 Percent of the World's Population and One Quarter of the World's Prisoners?" *The Washington Post*, April 30, 2015. <https://www.washingtonpost.com/news/fact-checker/wp/2015/04/30/does-the-united-states-really-have-five-percent-of-worlds-population-and-one-quarter-of-the-worlds-prisoners/>.

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