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PREDICTIVE ALGORITHMS AND CRIMINAL SENTENCING

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The legal and sociological study of judicial sentencing revolves around two broadly opposed conceptions of the relationship between existing laws and the decision-making process in courts. On the one hand, "internal" analyses describe judicial sentencing as the unproblematic application of a given set of legal rules. In this view, which encompasses the "legalist" ideology of the legal professions analyzed by Judith Shklar, judges, prosecutors, and attorneys are expected to implement a law that is always already "there," in ways that are objective, impartial, and consistent over time and across cases.¹ Most internal analyses thus focus on the formal characteristics of the laws themselves and pay scarce attention to the daily proceedings of the court system, which are considered to be unproblematic.

On the other hand, "external" approaches emphasize the indeterminacy of legal rules and highlight the role of nonlegal factors—political, social, and cultural—in shaping how laws are implemented in courts.² This is the case of "Legal Realist" perspective, an approach that emerged in the United States during the New Deal. Legal Realist scholars argued against the formalism of most legal analyses of judicial sentencing, noting instead that discretionary decision-making permeates the legal system. For instance, Jerome Frank, a prominent figure of Legal Realism, is often credited with the idea that judicial decisions mostly depend on what the judge had for breakfast. This "external" perspective in turn continues to influence most sociological analyses of judicial sentencing.³

Over the past ten years, the question of judicial discretion has taken a new turn with the development of "Big Data" analytics and algorithms. There are currently more than sixty predictive tools drawing on large amounts of quantitative data in the US criminal justice system.⁴ Based on a small number of variables about defendants, either connected to their criminal histories (e.g., previous offenses, failure to appear in court, violent offenses, etc.) or socio-demographic characteristics (e.g., age, sex, employment status, drug history, etc.), the algorithms typically provide an estimate of an offender's risk of recidivism or failure to appear in court when on bail, often expressed in a range of "low" to "high" risk. These predictive algorithms (also called "risk-assessment instruments") are explicitly designed to "structure" the criminal decision-making process and curtain judicial discretion by providing a clear set of guidelines, scores, and recommendations to judges, prosecutors, and probation officers in charge of making decisions about cases.

Risk-assessment tools have attracted increasing attention, both positive and negative. On the positive side, journalists and advocates for predictive technologies emphasize the benefits of using "smart statistics" in order to reduce crime and improve a dysfunctional criminal justice system characterized by racial discrimination and mass incarceration.⁵ In this view, risk-assessment tools might help empty overcrowded jails by constraining judicial discretion and reliably identifying low-risk offenders who could be released. Drawing a parallel with the case of baseball, where the use of data-intensive techniques transformed the game, advocates argue that we need to start "moneyballing justice" and replace "conjecture" with "formulas."⁶ "Evidence-based sentencing," as it is often called, has already attracted significant bipartisan support among practitioners, nonprofit institutions studying criminal justice, and governmental bodies in the United States.⁷

On the negative side, critics emphasize the dystopian and problematic aspects of Big Data analytics. They point out that predictive algorithms imply convicting defendants based on crimes they have not committed yet, creating a situation not unlike the one described by the film *Minority Report*.⁸ Critics argue that algorithms tend to reinforce social and racial inequalities instead of reducing them; they also note that risk-assessment tools draw on variables that are unfair and unconstitutional.⁹ More broadly, risk-assessment tools are analyzed as being part of a new "culture of control" based on the surveillance, prediction, and control at a distance of "risky" groups through actuarial techniques and digital technologies.¹⁰

Yet in all of this, there has been little research so far about what predictive tools mean for the conceptualization of judicial sentencing.

Are predictive algorithms putting an end to judicial discretion, turning sentencing into the application of a set of predefined rules? Or are they simply changing the form and locus of sovereign decision-making in the criminal justice context? More broadly, what are the representations and imaginaries of judicial sentencing embedded in predictive technologies, and what is the response of legal professionals? Moving beyond the history of decisionism, this chapter examines a modern debate surrounding algorithmic sentencing, a technology hailed by its proponents as capable of rationalizing aspects of the criminal justice system by detaching them from political considerations. First, I analyze the discourses surrounding the emergence of Big Data analytics in the US criminal justice system using the concept of "mechanical objectivity" developed by Daston and Galison.¹¹ The chapter then turns to the actual practices associated with risk-assessment tools. After listing the different types of predictive algorithms and actuarial techniques currently in use in criminal justice — and noting that many of them are not new -I offer a critical assessment of the main issues associated with the construction and reception of predictive algorithms in criminal justice. Specifically, I identify five major issues: algorithmic bias, heterogeneity and disparity, black boxing, gaming strategies, and changing values of punishment. I conclude by discussing avenues for future research on algorithmic decision-making, within and beyond the criminal justice context.

Making Sense of Big Data Analytics: The Myth of Mechanical Objectivity

"Big Data" has become a ubiquitous concept over the past ten years. According to boyd and Crawford,¹² three criteria need to be taken into account in analyzing the concept. First, Big Data encompasses a variety of new technologies involving the use of complex computational methods to analyze large data sets, themselves characterized by the three Vs: "volume" eccedented amounts of data), "variety" (the data frequently has eccedented amounts of data), "variety" (the data is frequently added over time). Second, Big Data involves novel forms of analysis and authority: the examination of large data sets, especially those where the entire population is included ("N=all"), makes it possible to identify new patterns that can later be used to make economic, social, technical, and legal claims. Third, Big Data functions as a mythology: it comes with a "widespread belief that large data sets offer a higher form of intelligence and knowledge."¹³ An illustration of this belief is the idea that, with Big Data, "the numbers speak for themselves," as Chris Anderson, then editor-in-chief of *Wired*, famously declared in his 2008 article on the "end of theory."¹⁴

Big Data and the Transformation of Decision-Making

Big Data analytics are currently transforming many areas of social life, from finance to communications, healthcare, education, journalism, policing, and, of course, criminal justice.¹⁵ There are significant similarities in the arguments developed to justify and advocate for algorithms across these sectors: algorithms are usually described as a rationalizing force.¹⁶ However, on a deeper level, two slightly different versions of this argument emerge. First, there is what can be called an "information" argument: in this view, algorithms are simply better than humans at gathering and analyzing large amounts of data. Therefore, algorithms make better decisions than individuals, simply because they have more information at their disposal, which they can compute and analyze in a faster and more reliable manner. For instance, in the case of credit and loans, the adoption of credit scores in the United States was described as an improvement compared to the traditional way in which banks made decisions about credit and mortgage.¹⁷

A second argument relates to the purportedly "objective" nature of algorithms: algorithms would be better than humans at making decisions because they are value-neutral. In this view — and in contrast to individuals, whose opinions are shaped by a variety of social factors including class, gender, race, age, politics, etc. — algorithms would have no politics: their goal would be to analyze data in the most accurate way and maximize the amount of variance explained by the model. Therefore, Big Data analytics are often described as the cure for systems shaped by long histories of discrimination. This argument can be found in the case of credit mentioned before: the different companies promoting credit scores described them as a less biased and discriminatory method for calculating financial risk than face-to-face interviews. This argument is also mobilized for public services such as education, policing, public administration, and, perhaps unsurprisingly, criminal justice.

Both the "information" and the "objectivity" arguments reflect a belief in the superior value of "mechanical objectivity" — which Daston and Galison define as "the insistent drive to repress the willful intervention of the artist-author, and to put in its stead a set of procedures that would, as it were move nature to the page through a strict protocol, if not automatically" — over human judgment.¹⁸ Like the scientists of the late nineteenth century who began relying on daguerreotypes and cameras in order to better represent nature, modern-day technologists, practitioners, consultants, and policy-makers strongly believe that machines are better than humans at making decisions and that they can process more information in an efficient, rational, predictable, and value-neutral way.

Justifying the Use of Big Data Analytics in the Criminal Justice System

This belief in the superiority of mechanical over human judgment is ubiquitous in the case of criminal justice. Advocates emphasize several benefits of Big Data analytics. Take, for example, the arguments developed by Anne Milgram, the former Attorney General for the State of New Jersey and former Vice President of Criminal Justice at the John and Laura Arnold Foundation where she supervised the development of a pretrial risk-assessment instrument. Milgram explained her views about "smart statistics" in an article published in The Atlantic and in a TED talk.¹⁹ Milgram points out that prisons are overcrowded and that this has become a significant problem, notably because of the costs incurred by taxpayers. According to her, courts currently do not have enough data about defendants and inmates: "Who is in our criminal justice system? What crimes have been charged? What risks do individual offenders pose? And which option would best protect the public and make the best use of our limited resources?"²⁰ Because judges and prosecutors do not have the answers to these questions, Milgram asserted, they rely on their problematic "instinct" when making decisions:

Judges have the best intentions when they make these decisions about risk, but they're making them subjectively. They're like the baseball scouts twenty years ago who were using their instinct and their experience to try to decide what risk someone poses. They're being subjective, and we know what happens with subjective decision making, which is that we are often wrong. What we need in this space are strong data and analytics.²¹

Big Data analytics, in Milgram's view, can lead to more informed and objective decision-making on the side of judges and prosecutors: "Technology could help us leverage data to identify offenders who will pose unacceptable risks to society if they are not behind bars and distinguish them from those defendants who will have lower recidivism rates if they are supervised in the community or given alternatives to incarceration before trial."²² This, in turn, would help "minimize injustice" in the criminal justice system: Our research has shown that the current system—which relies much more on subjective judgment than objective, evidence-based tools—does not adequately protect the public or ensure fairness. Defendants that you would expect to be locked up while awaiting trial—the very highest-risk individuals and those accused of violent crimes—are often released. Meanwhile, low-risk, nonviolent defendants often spend extended periods of time behind bars. This is counterintuitive and unfair, and it is putting our communities at risk.²³

Milgram's arguments are echoed by Adam Gelb, director of the public safety performance project at the Pew Charitable Trusts, who further emphasizes that risk-assessment tools make judges and prosecutors more accountable, therefore curbing prejudice and increasing the overall transparency of the system:

A supervisor can question, "Why are we recommending that this kid with a minor record get locked up?" Anything that's on paper is more transparent than the system we had in the past. In many cases, you had no idea from probation officer to probation officer, let alone from judge to judge, what was in people's heads. There was no transparency, and decisions could be based on just about any bias or prejudice.²⁴

Hence, advocates tend to understand Big Data analytics as a cure for a broken criminal justice system wo reasons. First, algorithms help judges and prosecutors make informed decisions about bail, sentencing, and parole by providing them with reliable information. Second, risk-assessment tools increase accountability by making the decision-making process more objective and transparent: legal professionals cannot solely rely on their "instinct" and "subjectivity." Thus, Big Data advocates strongly believe in the benefits of "mechanical objectivity" and the idea that human judgment can be improved by relying on data-driven, value-neutral algorithms. In so doing, they hope to eradicate or at least limit the discretion involved in judicial sentencing.²⁵

Risk-Assessment Tools in the United States: An Overview

Moving away from the discourses and arguments supporting Big Data analytics, I turn to the concrete technological artifacts that are being developed and used in the United States. Risk-assessment instruments are not new and indeed have existed for most of the twentieth century.²⁶ Yet the number of instruments, methods used, and diffusion across jurisdictions has expanded exponentially over the past twenty years. Whereas early instruments relied only on "static," unalterable factors (e.g., history of substance abuse, age at first offense, etc.), recent

instruments also draw on large data sets, increasingly sophisticated methods, and "dynamic" risk factors (e.g., variables about employment, criminal friends, etc., also called "criminogenic needs") that can be adjusted over time. The main risk-assessments tools currently in use in the US criminal justice system operate at three different stages of the criminal procedure: pretrial, sentencing, and probation.

In pretrial justice, the Arnold Foundation launched in 2015 the "Public Safety Assessment-Court" (PSA), a risk-assessment tool that can be used in every jurisdiction in the United States 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 instrument relies on variables such as the age of the defendant, his or her criminal record, and previous failures to appear in court. Contrary to other types of risk-assessment tools, it does not use variables about the individual's level of education, socioeconomic status, and place of residence. Before the PSA-Court, only about 10 percent of courts had developed their own risk-assessment tools. The Arnold Foundation's PSA pretrial instrument is currently used by twenty-nine jurisdictions, including three entire states (Arizona, Kentucky, and New Jersey) and three major cities (Charlotte, Chicago, and Phoenix). According to the Arnold Foundation, the PSA led to lower crime rates and a decrease in jail population in the jurisdictions where it was used.²⁷

A second area where risk-assessment tools are important is judicial sentencing itself. Efforts to standardize and limit disparities in sentencing are not new in the United States.²⁸ In 1984, for example, bipartisan efforts led to the Sentencing Reform Act, which created the US Sentencing Commission and the Sentencing Tables.²⁹ Though technically not a predictive tool (its main goal was to promote sentencing consistency by providing an average estimate of the sentences across jurisdictions in the United States), the Sentencing Tables nonetheless bear similarities with risk-assessment instruments: the columns categorize the criminal history of the defendants, while the rows describe their offense level, and each box provides an estimate of the mandatory length of incarceration (for example, ten to sixteen months of imprisonment). The <u>Sentencing</u> Tables became advisory instead of mandatory in 2005, (ut hany risk-assessment instruments have emerged since then to compute ment them. For instance, Pennsylvania's Sentencing Commission is developing a risk-assessment scale to determine what level of recidivism risk is associated with all adult defendants.³⁰

Finally, the number of states using a risk-assessment tool for probation and parole increased from about one in 1979 to more than twenty-eight since 2004.³¹ Among the most popular prediction instruments are the Level of Services Inventory-Revised (LSI-R), a proprietary product of the private company Multi-Health Systems; the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS), a product of Northpointe, Inc.; and the Salient Factor Score, used by the US Parole Commission. The types of variables included in these programs vary but are generally encompassing. For instance, Starr notes that "the LSI-R include 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."³² These tools are used for many purposes, including the security classification of prison inmates, inmates' eligibility for parole, and inmates' levels of probation and parole supervision.

Five Issues with Risk-Assessment Tools

This section identifies five sets of problems with the risk-assessment tools currently in use in the US criminal justice system: algorithmic bias, disparity and heterogeneity, black boxing, gaming and shifting discretion, and the changing goals of punishment. These issues point toward a disconnect between the optimistic beliefs regarding the benefits of Big Data analytics and the actual practices surrounding the construction, diffusion, and use of predictive algorithms.

Statistical Bias and Algorithmic Fairness

One of the main arguments used to justify the development and diffusion of risk-assessment tools is that algorithms would be more objective and value-neutral than people. In this view, algorithms would help "cure" administration marked by long histories of inefficiency and racial discrimination, two issues that well describe the US criminal justice system.³³ Yet it is not clear whether algorithms actually fulfill this goal. At a basic level, it is important to note that algorithms always draw on past data, which is itself biased in ways that mirror the discriminatory features of the existing system. Therefore, an uncritical use of algorithms at best reproduces the status quo; at worst, they may engage in "unintentional discrimination," have a disparate impact on different groups, and even increase inequalities between groups.³⁴

This is because algorithms tend to have a performative quality: they contribute to create the situation they describe. The case of predictive

policing is a clear instance of such a self-fulfilling mechanism. When predictive algorithms identify "hot spot" crime zones (usually low-income African American neighborhoods), policemen are more likely to patrol in these neighborhoods and arrest people who will later be convicted. If they never patrol in neighborhoods not identified as "hot spots" by the algorithm (for instance affluent neighborhoods), policemen will not make arrests in those places. This data will later be entered into the algorithm, thus producing a feedback loop: inner-city neighborhoods will be more frequently identified as "hot spots," which will shape the allocation of police effort, the arrests, and the algorithm's identification of "risky" versus "safe" zones. Harcourt describes this mechanism as a "ratchet effect": "the profiled populations become an even larger portion of the carceral population."³⁵

Understanding precisely how statistical bias operates in the case of risk-assessment tools requires us to get a sense of how they are constructed. In order to build a risk-assessment tool, one first needs a dataset made up of criminal cases that have already been sentenced. Based on this data set, statisticians or computer programmers run a model and select the variables that are the most significant in explaining the outcome variable of interest, such as recidivism or failure to appear in court. As in all other types of statistical analysis, dealing with a small sample size or a large amount of missing data (e.g., cases for which variables such as age, criminal record, etc., are lacking) is a challenge because it makes the model less accurate. Statisticians also need to decide which modeling strategy to adopt, from linear regression to machine learning techniques where the algorithm automatically adapts its equation to take into account new cases and follows specific procedure to analyze the data (decision tree, neural network, random forest, etc.).³⁶ 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: 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").³⁷

Thus, the mere fact that an algorithm does not include race as a variable in the model does not preclude it from having a discriminatory effect. None of the sentencing instruments or datasets mentioned above includes race as a variable. Yet many variables included in the models target ethnic minorities disproportionately (albeit unintentionally): they play the role of "proxies" for race, that is, they strongly correlate with race in the data set. For example, variables

about 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 end up having a stronger impact on specific groups, most importantly protected classes. Following this statistical line of reasoning, defendants are then sentenced based on their belonging to a specific group with "risky" characteristics rather than because of their individual actions, which goes against the jurisprudential value of individualism.³⁸ This, in turn, goes further than race. For example, most risk-assessment tools take gender, age, educational attainment, and socioeconomic background into account in their algorithm. As former US Attorney General Eric Holder poi out, "By basing sentencing decisions on static factors and immuta $\mathbf{\mathcal{V}}$ characteristics-like the defendant's education level, socioeconomic background, or neighborhood—they may exacerbate unwarranted and unjust disparities that are already far too common in our criminal justice system and in our society."39

It has even been argued that this type of statistical sentencing is unconstitutional, because people have the right to be treated—and sentenced—as individuals and not because they belong to a group with specific characteristics.⁴⁰ 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."⁴¹ In 2003, the America Civil Liberties Union 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."⁴²

Heterogeneity and Disparity

A second issue regards the heterogeneity and disparity of risk-assessment tools depending on the jurisdiction. A wide range of actors contributes to the construction and implementation of algorithmic sentencing in the United States. These include governmental organizations, nonprofit organizations, and private corporations, all of which have different resources and objectives. Technology developers also 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.

Thus, depending on the financial means of the organization constructing the algorithm and the size of the jurisdiction concerned, the quality of the algorithm will vary, together with the size of the data set, the amount of missing data, and the modeling techniques used. For example, the Arnold Foundation's PSA pretrial instrument uses a database of over 1.5 million cases from three hundred jurisdictions. Other instruments only rely on a few 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.⁴³ These differences in resources and methods come with significant variation between the algorithms and the variables that they take into account. For instance, whereas the Arnold Foundation's PSA-Court pretrial instrument only considers variables having to do with the criminal history of the defendant and her age, the Virginia Pretrial Risk Assessment Tool 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.⁴⁴ Other risk-assessment tools even include a quick psychological survey and take into account so-called "subjective" variables, which are defined by psychologists, about the defendant's "emotional status" or "personal attitude."⁴⁵

This piecemeal adoption of sentencing algorithms, developed using different methods and drawing on distinct variables, raises sig icant questions about the fairness of the judicial system as a who Will wealthier jurisdictions have more sophisticated predictive instruments than poorer jurisdictions? Will it make a difference for defendants to be sentenced in one jurisdiction rather than another because one or the other has a more punitive algorithm? Of course, judges also vary widely in their sentencing decisions, a fact that lawyers know well since they developed an online rating system for judges and jurisdictions.⁴⁶ Yet the crystallization of such disparities into the design of the algorithms is likely to harden inequalities between jurisdictions. Following former US Attorney General Eric H. Holder's 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," it is therefore important to consider whether or not the current proliferation of risk-assessment tools might contribute to increasing sentencing disparities between jurisdictions.47

Algorithmic Accountability and Black Boxing

Optimistic discourses surrounding the development of risk-assessment tools in the criminal justice system—support Anne Milgram's often rely on the rhetoric of accountability. In view, the adoption of risk-assessment tools would make judges and prosecutors more accountable by forcing them to justify their decision when they differ from the "objective" and "value-neutral" predictions of the algorithms. Risk-assessment tools are therefore presented as adding a layer of transparency to the judicial decision-making process on top of existing safeguards such as written reports and appeal procedures.⁴⁸

Yet many algorithms belie this hope for transparency and accountability.⁴⁹ In fact, most risk-assessments tools suffer from three different kinds of opacity.⁵⁰ The first form of opacity is intentional secrecy on the part of the organizations that construct, use, and sell the algorithms. Risk-assessment algorithms are usually proprietary products: most actors (nonprofit companies, for-profit companies, and jurisdictions) refuse to share either the algorithms or the training data sets that were used to create them, arguing that they do not want their products to be imitated. Second, opacity is connected to technical illiteracy: an overwhelming majority of actors using the algorithms do not have the technical skills to read or write code. This is particularly relevant in the case of criminal justice, since most legal professionals have no training in computer science. The third form of opacity is specific to machine-learning algorithms. Algorithms relying on machine-learning techniques are constantly evolving as new data is fed into the system. Consequently, even the computer programmers who built the algorithms are frequently in the dark regarding the specific procedures through which the algorithm achieves a given result.

Because of these different forms of opacity, there is a risk of what Pasquale calls "black boxing": important social, political, and ethical questions about sentencing decisions are not asked, because no one understands how the algorithm works.⁵¹ The metaphor of the black box describes a complicated system that is opaque to its users. Thus, defendants and their lawyers do not have access to the algorithms, do not know which risk score they receive, do not understand the reasons why they receive a given score, and do not have the possibility to appeal when they disagree with the score included in their file.

Gaming Strategies and Shifting Discretion

The first three issues raised here about risk-assessment tools were related to the construction side. I now examine how risk-assessment tools are used in courts. One of the main arguments developed by advocates of data-driven sentencing is that algorithms reduce discretion: they argue that quantification helps hold judges and prosecutors accountable for their decisions. But little is known about the efficacy of such interventions. Historical examples can in fact be introduced as cautionary tales. Consider the dynamics surrounding Sentencing Guidelines, a process intended to address earlier concerns about discretion, bias, and disparity in sentencing. Beginning in the mid 1960s, a broad bipartisan movement emerged to promote sentencing reform. Left-wing advocates believed that existing disparities in sentencing revealed overt discrimination and a punitive mindset among judges. Right-wing groups, meanwhile, argued that judges were too lenient and saw them as the primary culprits for rising crime rates. Both groups thought that determinate sentencing—the use of predefined sentencing ranges—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.

Yet 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 Sentencing Commission kept changing the Guidelines to take into account new categories of offenses; a more complex system of exceptions and reductions emerged over time, which judges struggled to follow and implement. Prosecutors, however, were not constrained at the Guidelines.⁵² They saw instead a significant increase in the ative decision-making power: they were the ones who decided on the charges that would then constrain the decision of the judges, because the charges would in turn determine the "Offense Level" column in the Sentencing Tables. Over time, the increasing number of criminal cases and overload of the court system led to a dramatic increase in plea-bargaining, a mechanism in which prosecutorial rather than judicial discretion reigns. Today, 97 percent of cases do not go to trial: they end in a plea bargain with a prosecutor.53

In other words, discretion did not disappear with the Sentencing Guidelines. Instead, it shifted to the prosecutors, who learned to manipulate offense charges and then present the results to the defendants in order to gain additional leverage in plea-bargain negotiations. 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.⁵⁴ Learning from

the case of the Sentencing Guidelines should encourage us to ask similar questions about the of algorithmic sentencing. Instead of assuming that risk-assee int tools will necessarily 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 these might entail.

In their work on legal rankings, Espeland and Sauder define "gaming" as "manipulating rules and numbers in ways that are unconnected to, or even undermine, the motivation behind them. Gaming is about managing appearances and involves efforts to improve ranking factors without improving the characteristics the factors are designed to measure."⁵⁵ Such "gaming strategies" have already emerged in the uses of risk-assessment tools. For instance, Hannah-Moffat and her colleagues find that legal professionals who use the LSI-R "adjust the assessment of criteria in order to control the final score, rather than relying on formal overrides."⁵⁶ In other words, probation officers tend to manipulate the variables entered in the instrument in order to obtain the score that they think is adequate for a given defendant, based on their instinct (or "clinical" expertise, as practitioners call it). According to Hannah-Moffat, this can:

lead to "criteria tinkering" (adjusting the rating of individual items when filling out the forms), for which there is no recorded accountability. This result also clearly demonstrates that practitioners continue to rely on their own discretion, selectively using responses to interpret, target, and isolate facts about past experiences and to make claims about the probability of reoffending to affect the risk score.⁵⁷

Gaming strategies complicate the accountability of algorithms. Thus, we should ask who will be responsible for filing the names and characteristics of the defendants into the software program. Who will be reading and interpreting the results? Which strategies will people use to change the settings of the risk-assessment tools when a result does not match their intuitions? Examining such questions is crucial in order to understand how evidence-based instruments affect the objectivity, transparency, and accountability of criminal sentencing.

The Changing Goals of Punishment

A last question regards the neutrality of risk-assessment tools, the values that are actually embedded in predictive algorithms, and the effects that such tools have on the goals and practices of punishment. In the criminal justice literature, punishment is traditionally analyzed as having four main justifications: retribution (punishment is justified because offenders have harmed society; their punishment should be commensurate with the crime committed); incapacitation (society has the right to be protected from offenders; punishment removes the possibility for offenders to commit further offenses); deterrence (the cost of punishment will properties and potential offenders from committing future offered and rehabilitation (punishment includes efforts to reform and rehabilitate offenders so that they will not commit the crime again).

Researchers have shown that the relative weight of these different goals of punishment is prone to change depending on the period, country, and political climate. In the lineage of Michel Foucault's work, scholars have mapped the development and consolidation of a "culture of control" in the United States and United Kingdom since the 1980s.⁵⁸ This new paradigm for punishment draws on a rather heterogeneous set of strategies and arguments, including an increasing reliance on mass incarceration, a punitive view of justice based on incapacitation and deterrence ("*prison works*," "*lock them out*," "*three strikes and you're out*"), the growing legitimacy of cost-benefit analyses of crime, and the rise of a system of surveillance and discipline through actuarial instruments and, more recently, digital technologies.⁵⁹

Unsurprisingly, risk-assessment tools are frequently seen as part of the current "culture of control": the tools take advantage of digital technologies and rely on actuarial techniques in order to analyze defendants' likelihoods of recidivism. Risk-assessment tools, in this view, function as a technology of governmentality: they operate at a distance, through statistical analysis, defining classes of individuals who are more or less "risky" and should be controlled more or less forcefully.⁶⁰ In addition, most predictive instruments emphasize one major justification at the detriment of the others: incapacitation, that is, a view of justice based on estimating the risk to society posed by the offender when deciding on a sentence designed to incapacitate dangerous individuals. Recent initiatives in juvenile justice have tried to include rehabilitation ideals in risk-assessment instruments.⁶¹ Yet, with the exception of the juvenile justice system, most predictive algorithms overwhelmingly focus on incapacitation rather than rehabilitation.

Do these broad penal changes also affect the concrete practices of sentencing? Practitioners and risk-assessment advocates say that algorithms merely provide "indicative" recommendations. Most judges and prosecutors argue that they do not blindly follow the results provided by algorithms when making a decision about an individual offender: they take into account all aspects of punishment when making sentencing decisions. In their view, risk-assessment tools merely provide information about the "incapacitation" aspect; legal professionals rely on their expertise and clinical experience to assess the defendant's personality and situation.

Yet it may be hard to "override the algorithm." In fact, judges and prosecutors are likely to "trust the numbers" and follow the recommendations provided by risk-assessment tools.⁶² The quantitative assessment provided by a software program alw preems more reliable, "objective," and scientific than other sour f information, including one's feelings about an offender, returning us to the complex of ideas about mechanical objectivity evoked above.⁶³ This is not only the case for laymen, but also for highly trained professionals: it is hard to challenge numbers and equations when one has not been trained in statistics. Thus, legal professionals may confuse correlation with causation, assigning strict causal influence to variables that merely affect the likelihood that a defendant will reoffend.⁶⁴

Judges and prosecutors might also override the algorithmic information in biased ways. A recent report on juvenile justice shows that "detain overrides" (i.e., a judge's decision to incarcerate a defendant when the algorithm recommends release) are more frequent than "release overrides" (e.g., the decision to release a defendant when the algorithm recommends incarceration).⁶⁵ 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 argued, "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.⁶⁶ If the recommendations of the algorithms are higher than the ones that judges had in mind, they might increase their sentences without realizing that they are trying to match the algorithm. Hence, risk-assessment tools are not the value-neutral objects that advocates paint them to be: they crystallize specific political ideas about the role of punishment.

Conclusion

This chapter examined the recent development of predictive algorithms in the US criminal justice system. I first analyzed the discourses surrounding risk-assessment tools, which many advocates describe as a rationalizing force designed to "structure" judicial sentencing. In this view, algorithms can help cure "broken" systems by providing more information and increasing the transparency, accountability, and objectivity of the criminal justice system. After introducing the main risk-assessment tools currently in use in the United States, I offered a critical examination of the main issues associated with the construction, diffusion, and use of predictive algorithms. These include: algorithmic bias and the problem of fairness; heterogeneity and the question of disparity between jurisdictions; black boxing, accountability, and lack of transparency; gaming strategies and shifting discretion; and the political values embedded in predictive algorithms and how they contribute to changing the goals of punishment.

More broadly, this discussion of the debates surrounding the use of risk-assessment tools in criminal justice reveals how long-standing questions about the nature of decision continue to inform recent developments related to algorithmic technologies. Is judicial sentencing primarily the application of a set of rules? Or is it essentially an informed but discretionary act? In a way, risk-assessment instruments merge these two conceptions: algorithms do apply specific rules to compute quantitative outcomes; such outcomes are in turn designed to provide condensed information to the decision-maker-be it a judge, a prosecutor, or a probation officer—with the goal of making discretionary judgment more informed. In other words, not unlike the "Law & Economics" movement in the 1970s-1980s, Big Data advocates are hoping to transform both the technological infrastructure of courts and the cultural framing of judicial sentencing.⁶⁷ Yet a closer analysis of risk-assessment tools indicates that sovereign decision-making never vanishes from the picture. Not only do judges and prosecutors selectively ignore the outputs provided by the algorithms; the construction of the algorithms themselves is fraught with political decisions, including which model to choose, which variables to include, and which outputs to measure.

There is an interesting continuity between the arguments developed in the second half of the twentieth century to depoliticize decision-making—most importantly cybernetics and game theory, two perspectives at the center of several chapters of this volume—and the arguments used to justify Big Data algorithms. Similar claims about objectivity, neutrality, rationality, and technical efficiency can be found in all cases; similar criticisms also emerge. Future research might consider how different expert groups take on the mantle of rationalizing administration by considering the parallels between economists in the past decades and data scientists today. Are economists being trained in Big Data methods? Are "data scientists" —the "sexiest job" of the twenty-first century, according to the *Harvard Business* *Review*—simply replacing economists as the main providers of rationality in the political arena, in the same way that economists replaced lawyers after World War II?⁶⁸ These are some of the larger questions raised by the reconfiguration of expertise and decision-making in the criminal justice system.

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