

Risk-Assessment Tools in the U.S. Criminal Justice System:

Construction, diffusion, and uses¹

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Abstract

One of the most striking innovations in the criminal justice system during the past thirty years has been the introduction of actuarial methods – statistical models and software programs – designed to help judges and prosecutors assess the risk of criminal offenders. Predictive algorithms are currently used in four major areas of the U.S. criminal justice system: pretrial and bail, sentencing, probation and parole, and juvenile justice. These algorithms consider a small number of variables about a defendant – either connected to her or his criminal history (previous offenses, failure to appear in court, violent offenses, etc.) or socio- demographic characteristics (age, sex, employment status, drug history, etc.) – in an effort to predict a defendant’s risk of recidivism or their likelihood to fail to appear in court if they are let out on bail. Advocates for increased use of actuarial instruments highlight their potential to automate and standardize decision-making processes by considering relevant risk factors. This article argues instead that there is an important gap between the normative goals and the actual consequences of data-driven sentencing.

Introduction

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 in the criminal justice system during the past thirty

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years has been the introduction of statistical models and software programs designed to help judges and prosecutors 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. Predictive tools are currently used at every step of the U.S. criminal justice system, from pretrial to sentencing, probation, and parole.³ Most risk-assessment tools used in courts draw on actuarial techniques developed in the insurance sector. Based on a small number of variables about the defendants, either connected to his or her criminal history (previous offenses, failure to appear in court, violent offenses, etc.) or socio-demographic characteristics (age, sex, employment status, drug history, etc.), the algorithms typically provide an estimate of an offender’s risk of recidivism or failure to appear when on bail, from “low” to “high.”

Advocates for these policies 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.⁴ Advocates also explain that risk-assessment tools make sentencing more transparent, reduce disparities in sentencing, and help curb racism and discrimination by making judges more accountable for consistent decision-making. Data-driven initiatives are said to minimize incarceration rates and length of imprisonment for low-risk offenders, resulting in lower budgetary costs and reduced social harm.⁵ Predictive

² Harcourt, Bernard E. 2006. *Against Prediction: Profiling, Policing, and Punishing in an Actuarial Age*. Chicago: University of Chicago Press, p. 39.

³ For an overview, see http://fivethirtyeight.com/features/prison-reform-risk-assessment/?ex_cid=fusion

⁴ According to a 2000 meta-study by a team of psychologists, experts who make decisions using statistical actuarial tools are 10% more accurate at predicting human behavior than experts who do not use such tools:

<https://www.psych.umn.edu/faculty/grove/096clinicalversusmechanicalprediction.pdf>

Recent research on the uses of actuarial risk assessment among federal probation officers confirmed these findings:

<https://www.ncjrs.gov/App/Publications/abstract.aspx?ID=258839>

⁵ http://www.nytimes.com/2015/06/27/us/turning-the-granting-of-bail-into-a-science.html?_r=2

<http://www.arnoldfoundation.org/minimize-injustice-use-big-data/>

<http://www.aecf.org/m/resourcedoc/aecf-JDAI2013AnnualResultsReport-2014.pdf>

algorithms are also presented as saving precious time for overworked prosecutors, judges, clerks, and other court staff.⁶

Evidence-based initiatives attract significant bipartisan support 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.⁷ Yet, scholars and critics have challenged the new “culture of control” based on the surveillance and prediction that such instruments promote.⁸ There are also concerns about limiting discretion, biases in the data, the accuracy of the predictions, and algorithmic accountability.

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.⁹ According to the most recent figures, 1 in 12 black men between 25 and 56 years old is currently in jail.¹⁰ 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 to curb discrimination and to improve the fairness of the system. Examining the concrete practices associated with the uses of predictive algorithms in courts is crucial to assessing the efficacy of this agenda.

⁶ https://www.bja.gov/publications/pji_pretrialriskassessment.pdf;

⁷ Starr, Sonja B. 2014. “Evidence-Based Sentencing and the Scientific Rationalization of Discrimination.” *Stanford Law Review* 66 (4): 803-871, here p. 815-816.

http://www.stanfordlawreview.org/sites/default/files/66_Stan_L_Rev_803-Starr.pdf

⁸ 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; Feeley, Malcolm M., and Jonathan Simon. 1992. “The New Penology: Notes on the Emerging Strategy of Corrections and Its Implications.” *Criminology* 30 (4): 449-74.

For critical media coverage, see <http://www.truth-out.org/news/item/29818-moneyballing-justice-evidence-based-criminal-reforms-ignore-real-evidence>

⁹ <http://www.naacp.org/pages/criminal-justice-fact-sheet>;

<http://www.prisonstudies.org/country/united-states-america>

<http://www.washingtonpost.com/blogs/fact-checker/wp/2015/04/30/does-the-united-states-really-have-five-percent-of-worlds-population-and-one-quarter-of-the-worlds-prisoners/>

¹⁰ http://www.nytimes.com/interactive/2015/04/20/upshot/missing-black-men.html?_r=0&abt=0002&abg=0

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 developed their own risk-assessment tools.¹¹ 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 led to lower crime rates and a decrease in jail population in the jurisdictions where it was used.¹²

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 sentences. The Sentencing Tables are based on a statistical analysis of the factors leading to recidivism: the columns categorize the criminal history of the defendant, while the rows describe her offense level, and each box provides an estimate of the mandatory length of incarceration (for example, 10-16 months of imprisonment).¹³ The Sentencing Tables became advisory in 2005. Many risk-assessment instruments have emerged since then. 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.¹⁴

¹¹ <http://www.arnoldfoundation.org/more-than-20-cities-and-states-adopt-risk-assessment-tool-to-help-judges-decide-which-defendants-to-detain-prior-to-trial/>

¹² <http://www.arnoldfoundation.org/more-than-20-cities-and-states-adopt-risk-assessment-tool-to-help-judges-decide-which-defendants-to-detain-prior-to-trial/>

¹³ See Harcourt, *op. cit.*; Espeland, Wendy Nelson, et Berit Irene Vannebo. 2007. “Accountability, Quantification, and Law.” *Annual Review of Law and Social Science* 3 (1): 21–43.

¹⁴ http://fivethirtyeight.com/features/prison-reform-risk-assessment/?ex_cid=fusion;
<http://pcs.la.psu.edu/publications-and-research/research-and-evaluation-reports/risk-assessment>;

3. *Probation and Parole*. The number of states using a risk-assessment tool increased from 1 in 1979 to 28 in 2004.¹⁵ The most popular prediction instrument is the LSI-R (Level of Services Inventory-Revised), a proprietary product of the private company Multi-Health Systems.¹⁶ As noted by law professor Sonja B. Starr, “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.”¹⁷ The LSI-R is 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 they mention that several causes might be responsible for this change.¹⁸ 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.¹⁹

<http://pcs.la.psu.edu/publications-and-research/research-and-evaluation-reports/risk-assessment/interim-report-7-validation-of-risk-scale/view>

¹⁵ Harcourt, *op. cit.*, p. 78.

¹⁶ <http://www.mhs.com/product.aspx?gr=saf&prod=lsi-r&id=overview>. Another widely-used instrument is the Salient Factor Score:

<https://www.ncjrs.gov/App/publications/abstract.aspx?ID=72196>

¹⁷ Starr, *art. cit.*, p. 813.

¹⁸ <http://www.aecf.org/m/resourcedoc/aecf-JDAI2013AnnualResultsReport-2014.pdf>

¹⁹ <https://chronicleofsocialchange.org/featured/floridas-new-predictive-risk-tool-likely-to-drive-down-juvenile-incarceration/10505>

Constructing the algorithms: different actors, varying methods

A wide and heterogeneous range of actors contributes to the construction and implementation of algorithmic sentencing in the United States, including governmental organizations – both federal and local – as well as non-profit organizations and private corporations. All of the 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? These methodological details are important for understanding why differences in resources matter. First, one needs a data set made up of criminal cases that have already been sentenced. Based on this data set, statisticians and computer programmers run a model and usually select the variables that are the most significant in explaining the outcome variable of interest (for example 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: sophisticated approaches rely on machine learning, where the algorithm automatically adapts its equation to take into account new cases, whereas more basic strategies rely on a static model. 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”).²⁰

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 sophistication of the modeling techniques used. For example, the Arnold Foundation’s PSA pretrial instrument

²⁰ <http://www.aecf.org/m/resourcedoc/aecf-juvenile-detention-risk-assessment1-2006.pdf> (p. 52)

uses a database of over 1.5 million cases from 300 jurisdictions. Other instruments only rely on 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.²¹

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, 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.²² 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.²³

Algorithms, fairness, and sentencing disparities

This proliferation and piecemeal adoption of sentencing algorithms developed using a wide range of methods raises significant questions about the fairness of the judicial system as a whole. 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? Depending on the methods, algorithms used in various jurisdictions might make different predictions about the danger of the same offender – influencing a judge to make different decisions about whether to incarcerate someone or not. Although these algorithms are not making judgments in lieu of judges, it is not yet clear how 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.

²¹ <http://www.aecf.org/m/resourcedoc/aecf-juvenile-detention-risk-assessment1-2006.pdf> (p. 12)

²² These variables can be found in the Virginia Pretrial Risk Assessment Instrument : <http://www.pretrial.org/download/risk-assessment/Risk%20Assessment.pdf>

²³ Starr, *art. cit.*, p. 812.

Following former Attorney General Eric H. Holder Jr.'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,”²⁴ it is important to consider whether or not the current proliferation of risk assessment tools might contribute to reducing sentencing disparities within jurisdictions and increasing sentencing inequalities between jurisdictions.

In addition, as a more radical critique, 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 target ethnic minorities disproportionately: they play the role of “proxies” for race (that is, they strongly correlate with race). For example, variables about a defendant’s place of residence (e.g. postal 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, including protected classes. Following this line of reasoning, defendants are then sentenced based on their belonging to a specific group rather than because of their individual actions. This goes further than race. For example, many risk-assessment tools take gender and age into account in their algorithm: men and younger defendants are statistically more likely to commit offenses than women and older defendants.

Sonja B. Starr argues 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 “risky” characteristics. 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.”²⁵ 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

²⁴ <http://www.justice.gov/sites/default/files/criminal/legacy/2014/08/01/2014annual-letter-final-072814.pdf>; <http://www.justice.gov/opa/speech/attorney-general-eric-holder-speaks-national-association-criminal-defense-lawyers-57th>

²⁵ Starr, *art. cit.*, p. 827.

of the fundamental Constitutional principles of equality and fairness.”²⁶ Several practitioners have disagreed with these positions, however, and maintained their support for risk-assessment tools that do not include variables about race in the models.²⁷

Yet 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 reduce discretion. These advocates argue that quantification helps to hold judges and prosecutors more accountable for their decisions. Algorithms are presented as an easy solution for making sentencing more transparent, consistent, and possibly less discriminatory. 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

²⁶ <http://acluva.org/1671/aclu-brief-challenges-constitutionality-of-virginias-sex-offender-risk-assessment-guidelines/> The case was dismissed by the State Court of Appeal, which argued that the risk-assessment tool was only advisory: <http://acluva.org/wp-content/uploads/2003/10/150604-VA-Court-of-Appeals-ruling-on-sex-offender-guidelines.pdf> http://fivethirtyeight.com/features/prison-reform-risk-assessment/?ex_cid=fusion

²⁷ <http://www.arnoldfoundation.org/minimize-injustice-use-big-data/>

solution. They supported the Sentencing Reform Act and the creation of Sentencing Guidelines, which were sponsored by Senator Ted Kennedy and passed in 1984.²⁸

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.²⁹

In other words, discretion did not disappear with the Sentencing Guidelines. Instead, it shifted to the 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.³⁰

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

²⁸ Espeland and Vannebo, *art. cit.* ; Harcourt, *op. cit.*

²⁹ Resnick, Judith, 2006. “Whither and Whether Adjudication.” *Boston University Law Review* 86: 1101-1154; Alexander, Michelle. 2010. *The New Jim Crow. Mass Incarceration in an Age of Colorblindness*. New York: The New Press.

<http://www.nybooks.com/articles/archives/2014/nov/20/why-innocent-people-pleadguilty/>

³⁰ Recent research by the Vera Institute found that Black and Hispanic defendants were significantly more likely to be offered plea deals on misdemeanors than were white or Asian defendants: http://www.nytimes.com/2014/07/09/nyregion/09race.html?_r=0; <https://www.ncjrs.gov/pdffiles1/nij/grants/247227.pdf>

filling the names and characteristics of the defendants into the software program? Who will be reading and interpreting the results? 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 intuitions? 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 how risk-assessment tools are used by judges and prosecutors: how can we make sure that algorithms will contribute to lower rates of incarceration and improve the fairness of the criminal justice system instead of worsening it?

According to advocates of evidence-based sentencing, algorithms merely provide “indicative” recommendations. 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 also rely on their expertise and clinical experience to assess her personality, situation, and risk of recidivism.

Yet existing research shows that it is difficult to “override the algorithm.” In fact, judges and prosecutors are likely to follow the recommendations provided by risk-assessment tools. A quantitative assessment provided by a software program always seems more reliable, scientific, and legitimate than other sources of information, including one’s feelings about an offender.³¹ 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 recommends release) are much more frequent than “release overrides” (e.g., the decision to release a defendant when the algorithm recommends incarceration).³²

Eventually, judges and prosecutors might change their sentencing practices in order to match the predictions of the algorithms. As behavioral economists Amos

³¹ Hannah-Moffat, Kelly, Maurutto, Paula, and Sarah Turnbull. 2010. “Negotiated Risk: Actuarial Assessment and Discretion in Probation.” *Canadian Journal of Law and Society*. 24 (3): 391-409. More generally, see Porter, Theodore M. 1996. *Trust in Numbers. The Pursuit of Objectivity in Science and Public Life*. Princeton: Princeton University Press.

³² <http://www.aecf.org/m/resourcedoc/aecf-juvenile-detention-risk-assessment1-2006.pdf> (p. 44-46).

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.³³ 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.

Perhaps even more problematic is the theory of justice implicitly embedded in the algorithms. Punishment is usually said to have four main justifications: retribution, incapacitation, deterrence, and rehabilitation. Risk-assessment tools emphasize one major justification at the detriment of the others: incapacitation.³⁴ 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. Retribution, deterrence, and rehabilitation – which emphasize instead the potential recovery of offenders and their inclusion in the social body – are not embedded in the current versions of the algorithms.

Although intended to do the opposite, there is a risk that risk-assessment tools may render criminal sentencing more punitive than it currently is, going against the goal of many advocates on the left who support evidence-based reform. This poses a set of important questions relating to how to encourage judges and prosecutors 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 results when needed?³⁵ How could we include non-repressive judicial goals in the statistical tools? These questions need to be raised before sentencing algorithms become completely institutionalized in their current form.

Conclusion: algorithms and the reconfiguration of expert judgment

This piece provides an introductory overview of the questions and challenges associated with the multiplication of predictive algorithms in criminal courts. It is part of a broader

³³ Tversky, Amos, and Daniel Kahneman. 1974. “Judgment Under Uncertainty: Heuristics and Biases.” *Science* 185 (4157): 1124-1131.

³⁴ Harcourt, *op. cit.*

³⁵ See for the example the idea that people are more likely to use and accept algorithms if they are able to modify them: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2616787

ongoing project about the reconfiguration of expert judgment drawing on the cases of criminal justice and journalism, which I briefly introduce below.

Over the past twenty years, many professions that were formerly protected from quantitative evaluation have been confronted with a multiplication of indicators measuring the performance and productivity of workers. In addition, professionals are increasingly required to follow standardized procedures in their daily work, which are often designed to curb discretion, to rationalize expert decisions, and to increase professional accountability. The recent development of Big Data analytics contributes to this new paradigm of professional expertise: algorithms typically provide detailed measurements of the performance of professionals in addition to rationalizing their work by providing “objective” recommendations. Algorithms drawing on Big Data have become central in the daily work of professionals in law, medicine, journalism, education, finance, as well as many other areas of expertise.

Yet the growing importance of algorithms in professional sectors does not necessarily entail that they have similar effects everywhere. Depending on the organization, the profession, and the national context under consideration, the same algorithm might be taken up with enthusiasm, resisted strongly, or be deemed irrelevant by those it was designed to measure. Thus, more research is needed comparing the reception and uses of algorithms in different professions. How do professionals make sense of algorithms? When do they resist such processes of quantification, and why?

My current project explores these questions by comparing the case of criminal justice and journalism. In both sectors, algorithms play an increasingly important role. In the criminal justice system, predictive algorithms drawing on actuarial models from the insurance sector help judges and prosecutors assess the “risk” of the defendants, from pretrial to sentencing, probation, and parole. “Evidence-based reform” has become mainstream in the United States and in Europe, in an effort to reduce bias and accelerate the decision-making process. Similarly, in online journalism, real-time analytics software programs now analyze which topics are trending and which articles should be promoted

in order to attract traffic and respond to the preferences of online readers.³⁶ Such algorithms primarily aim to help journalists better understand their audiences. Yet they are also frequently used to assess the productivity of individual journalists, which in turn affects their compensation and career prospects.

Drawing on multi-sited ethnographic fieldwork conducted at criminal courts and web newsrooms in the United States and France, completed by interviews with judges, prosecutors, journalists, and editors in the two countries, I develop two ideas. First, I argue that algorithms never eradicate professional discretion. Instead, based on the cases of criminal justice and journalism, I analyze how discretion shifts to new, surprising places in the organization. Second, I argue that resistance to algorithms varies depending three central criteria: how the algorithms are constructed (and which system of classification and ranking they offer); whether the profession has a strict monopoly on its area of expertise; and whether there is a central authority promoting the algorithms. I illustrate this idea with examples from criminal justice and web journalism in the United States and France. More broadly, this project hopes to cast doubt on the idea that algorithms rationalize expert knowledge and increase transparency in the professions, documenting instead the micro-level practices of professionals who often find ways to ‘game’ the algorithms in their daily work.

³⁶ See Angèle Christin, “Clicks or Pulitzers ? Web Journalists and Their Work in the United States and France,” Ph.D. Dissertation, Princeton University, Department of Sociology, July 2014.

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