

ALGORITHMIC RISK ASSESSMENTS: A LEVELING OR EXPANDING OF THE INCARCERATION PLAYING FIELD?

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Risk assessments tools have long been used in the justice system to assist decision-makers in determining whether an offender should be incarcerated pretrial or when an incarcerated individual is eligible for parole. With the growth and development of machine learning algorithms, naturally, these tools have turned into more efficient and, generally, accurate means of making these decisions. However, it is expedient to examine on what data and societal “rules” these algorithms are based. In some cases, these tools have built on injustices and systemic biases in society. They have further been without clear oversight due to their proprietary nature—companies ensure a “black box” of algorithmic calculations. In other cases, they have helped allay egregious incarceration rates, and proved to have positive results.¹ Still others are in their infancy and results are forthcoming.²

Part I discusses the history and need for risk assessments in the social justice context, and the development of actuarial and judicial assessments used for determining pretrial incarceration and recidivism risk. Part II looks at the modern-day tools framed around the *Loomis* case and what the current arguments are for and against use and accuracy of risk assessment algorithms.³ Part III is a commentary on the present legal questions facing the judicial system in light of *Loomis*, the weight of machines versus human judgment, and course-correcting suggestions that can pave the way forward.

PART I. PROFESSIONAL ASSESSMENTS AND SYSTEMIC DISPARITY

Recent books like *Just Mercy* and *The New Jim Crow* have shone a larger spotlight on pervasive systemic racism through incarceration and how policies instituted in the name of public safety have categorically and historically disadvantaged minorities,

¹ See *Winning Bail Reform in New Jersey*, DRUG POL’Y ALL., <http://www.drugpolicy.org/new-jersey/winning-bail-reform> (last visited Aug. 6, 2019).

² See Eric Westervelt, *California’s Bail Overhaul May Do More Harm Than Good, Reformers Say*, NPR (Oct. 2, 2018, 5:01 AM), <https://www.npr.org/2018/10/02/651959950/californias-bail-overhaul-may-do-more-harm-than-good-reformers-say>.

³ *State v. Loomis*, 2016 WI 68, 881 N.W.2d 749.

particularly young black men.⁴ Throughout the decades, this disproportionate punitive system has gone through many title changes: Jim Crow laws, “stop-and-frisk,” the war on drugs, and mass incarceration. Although this article will not discuss the laws and social implications surrounding these movements, it is important to note their relevance in risk assessment tools—this is the historical truth of our society, and from the historical truth comes data. Data is used for training machines and algorithms which will be examined in Part II.

The justice system itself early-on disproportionately affected minorities, low-level drug offenders, and those from lower socioeconomic classes in the form of setting a monetary bail the offender could not afford, or mandating incarceration for certain crimes regardless of history of violence.⁵ The effects of pretrial incarceration ripple throughout society in the form of higher recidivism rates correlating with length of incarceration, taxpayer funded jail costs, and a more burdened judiciary system.⁶ Detaining someone prior to trial who, under the law, is supposed to be presumed innocent is, according to the U.S. Supreme Court, a “carefully limited exception” to the liberties afforded by the Eighth Amendment.⁷ Such detention is determined by the offender’s risk of flight and potential danger to the community.⁸ Similarly, the granting of parole is determined by the offender’s level of risk to themselves and society based on numerous factors.⁹

Conventional offender risk assessment, both pretrial and post-conviction, reflects actuarial methods used by insurance and business companies to project and assess risk.¹⁰ Regarding whether an offender should be incarcerated or set on bail pretrial, judges have an enormous amount of discretion when sentencing. Because these decision-makers are human, they can also have an equal amount of external influences affect their processes including guidelines, schedules, and political

⁴ See generally BRYAN STEVENSON, JUST MERCY (2015); MICHELLE ALEXANDER, THE NEW JIM CROW: MASS INCARCERATION IN THE AGE OF COLORBLINDNESS (2011).

⁵ See THE OXFORD HANDBOOK OF PRISONS AND IMPRISONMENT 9 (John Wooldredge & Paula Smith eds., 2018) [hereinafter PRISONS AND IMPRISONMENT]; Richard F. Lowden, *Risk Assessment Algorithms: The Answer to an Inequitable Bail System?*, 19 N.C. J. L. & TECH., April 2018, at 221, 222-23.

⁶ Lowden, *supra* note 5 at 226-28.

⁷ Glen J. II Dalakian, *Open the Jail Cell Doors, Hal: A Guarded Embrace of Pretrial Risk Assessment Instruments*, 87 FORDHAM L. REV. 325, 332-33 (2018) (citing *U.S. v. Salerno*, 481 U.S. 739, 755 (1987)).

⁸ Lowden, *supra* note 5 at 227-28.

⁹ See *infra* Part II.

¹⁰ RICHARD BERK, MACHINE LEARNING RISK ASSESSMENTS IN CRIMINAL JUSTICE SETTINGS 31 (2019).

elections.¹¹ Parole boards will utilize risk assessments to determine when an inmate is eligible for release and frequency of visits with parolees—the less at risk, the earlier the release and the fewer the visits.¹² Historically, risk-related factors were given to parole boards without direction on how or how much these factors correlated with recidivism.¹³ Earlier on, retribution-focused assessment factors included static predictors that did not consider the potential for change or allow intervention like a dynamic factor would (i.e., education level or drug-addiction).¹⁴ Later, evidence-based practices were introduced and more dynamic factors were incorporated whereby determinations included not only risk, but the unmet needs of the offender that allowed treatment and intervention.¹⁵

The accuracy of these early tools relied mostly on human judgment, and thus, could not be immune from human error. While human judgment alone had its own faults, actuarial methods also posed unique problems. As criminologist Richard Berk explains, actuarial methods are used to “characterize how various properties of individuals and their immediate crimes are associated with different kinds of subsequent outcomes.”¹⁶ Those associations are then used to determine in what crime or risk class offenders should be placed.¹⁷ Implicit bias¹⁸ would be an issue when looking at both static and dynamic factors; but so would other factor- or data-based errors when using these actuarial methods including using incorrect base rates, incorrectly weighing information, failing to take into account covariation or regression to the mean, among other problems.¹⁹ When machine-based algorithms started taking over as assessment tools, they subverted actuarial methods, potentially judicial discretion, and, in some cases, the ability

¹¹ Daniel L. Chen, *Judicial Analytics and the Great Transformation of American Law*, 27 J. ARTIFICIAL INTELLIGENCE & L., March 2019, at 6-10; Dalakian, *supra* note 7, at 330.

¹² Jacob Curtis, *On Using Machine Learning to Predict Recidivism* 4 (May, 2018) (unpublished Ph.D. dissertation, Texas Tech University), <https://ttu-ir.tdl.org/handle/2346/73945>.

¹³ *Id.* at 9.

¹⁴ *Id.* at 10; *see* Dalakian, *supra* note 7, at 340.

¹⁵ Dalakian, *supra* note 7, at 340; Curtis, *supra* note 12, at 10.

¹⁶ BERK, *supra* note 10, at 42.

¹⁷ *Id.*

¹⁸ *See generally Understanding Implicit Bias*, KIRWAN INST. STUDY RACE & ETHNICITY, <http://kirwaninstitute.osu.edu/research/understanding-implicit-bias/> (last visited Aug. 7, 2019) (“[I]mplicit bias refers to the attitudes or stereotypes that affect our understanding, actions, and decisions in an unconscious manner.”).

¹⁹ Dalakian, *supra* note 7, at 331. A base rate is a statistic indicating the likelihood of an event occurring organically. The covariation or regression to the mean describes the chance event of extreme outliers occurring followed or preceded by events closer to the average.

to check the processes formerly described.

PART II. THE MODERN ERA OF RISK ASSESSMENT

Overall, modern risk assessment tools have aided judges, parole boards, and prosecutors in making informed decisions based on certain factors. There is evidence that use of some of these forecasts allowed for smarter decision making, improvements in public safety, and reductions in re-arrests.²⁰ However, algorithmic misuse and accuracy are the two biggest problems facing the burgeoning technological tool usage. They can violate constitutional rights and compound societal biases if these missteps continue without oversight.

A. *Loomis* holdings on assessment tool utilization indicate unclear future with potential constitutional violations if misused

State v. Loomis has become the preeminent case on algorithmic-based sentencing and assessment.²¹ In it, defendant Eric Loomis was sentenced to prison for six years based on, among other things, the input given from a proprietary risk assessment tool called COMPAS (Correctional Offender Management Profiling for Alternative Sanctions). He appealed the sentence arguing that the use of COMPAS violated his due process rights since it utilized gender as a factor, the proprietary nature of the tool prevented him from challenging the validity, and that it relied on group data rather than individualized assessment.²² The Wisconsin Supreme Court held that *proper* use of the tool was not violative of due process, such as here, particularly when supported by other independent factors.²³

Although the weighing of the factors is concealed in what is known as the “black box” of machine algorithms, the input is known by the offender, which the court holds is verification enough.²⁴ In the case of COMPAS, the input factors are primarily static ones dealing with previous arrest(s), with limited use of dynamic factors such as criminal associates or substance abuse.²⁵ Further, the data that COMPAS weighs is based on a comparison of the individual’s inputs against group data: “an individual who has never committed a violent

²⁰ Richard Berk, *An Impact Assessment of Machine Learning Risk Forecasts on Parole Board Decisions and Recidivism*, 13 J. EXPERIMENTAL CRIMINOLOGY, June 2017, at 213.

²¹ *Loomis*, *supra* note 3.

²² *Id.* at ¶¶ 6, 67.

²³ *Id.* at ¶¶ 8-9.

²⁴ *Id.* at ¶¶ 53-55.

²⁵ *Id.* See also Leah Wisser, *Pandora’s Algorithmic Black Box: The Challenges of Using Algorithmic Risk Assessments in Sentencing*, 56 AM. CRIM. L. REV. 1811, 1816 (2019).

offense may nevertheless be labeled as a high risk for recidivism on the violent risk scale.”²⁶ The court continues to lay out, through dicta, what limitations should be applied when utilizing risk assessment tools like COMPAS, which includes not using the algorithm to determine incarceration or severity of sentencing.²⁷

This case has brought to light the legal questions facing users of algorithmic risk assessment that compromise due process in the context of both the Fifth and Fourteenth Amendments, as well as potentially the Sixth and Eighth Amendments. So, how do we determine if technology, in this case, is truly the better or more efficient route than human pronouncements? Why do we hold algorithms to a stricter standard than judicial decision-making?

B. The current playing field of risk assessment algorithms is still emerging and grappling with acceptable accuracy rates

Hundreds of tools have been developed over the years to assess risks of violence and offending; they vary by state and by the stage in the criminal justice system at which the risk is being assessed.²⁸ Violent offense risk forecasting is produced by training algorithms on large datasets and correlating features with outcomes, developing associations between inputs and outputs.²⁹ Besides COMPAS, other notable automated systems include Level of Service Inventory (LSI), Post Conviction Risk Assessment (PCRA), and Public Safety Assessment (PSA).³⁰ The PSA has been deemed a universal application that can be applied to “front-end and back-end situations”—a concerning problem that utilizes the same factors and possibly weights of factors, but for different applications.³¹ Although these tools are more accurate than past professional assessments used, they are not without their own complexities.

Studies have shown that these processes have resulted in disproportionate outcomes against disadvantaged groups—most notably against people of color.³² However, no assessment tool

²⁶ *Loomis*, *supra* note 3, at ¶ 69.

²⁷ *Id.* at ¶ 98.

²⁸ Han-Wei Liu et al., *Beyond State v. Loomis: Artificial Intelligence, Government Algorithmization and Accountability*, 27 INT’L J. L. & INFO. TECH., Summer 2019, at 125-26; Jodi L. Viljoen et al., *Do Risk Assessment Tools Help Manage and Reduce Risk of Violence and Reoffending? A Systematic Review*, 42 L. HUMAN BEHAVIOR 181, 181 (2018).

²⁹ BERK, *supra* note 10, at 170.

³⁰ See Liu et al., *supra* note 28, at 125-26.

³¹ Dalakian, *supra* note 7, at 345.

³² See Bruno Lepri et al., *Fair, Transparent, and Accountable Algorithmic Decision-Making Processes: The Premise, the Proposed Solutions, and the Open Challenges*, 31 PHIL. & TECH., Dec. 2018, at 611, 612; Julia Angwin et al., *Machine Bias*,

explicitly uses race as a factor; rather, other inputs such as criminal history, zip code, and socioeconomic status may have become proxies for it.³³ In Jacob Curtis’s dissertation study, he found that neither race nor age were particularly important in the accuracy of predicting recidivism.³⁴ Technically speaking, there are no inaccuracies with the data itself; however, the data reflects a society and an implicit bias that has systemically disadvantaged minorities, poor people, and those with mental or drug-related illnesses. For example, take two neighborhoods with similar crime rates, one predominantly white and the other predominantly black or brown—predictive policing will overestimate crime rates in neighborhoods with minorities, so while the crime rates are similar, the crime *observed* will be higher in those neighborhoods, leading to higher incarceration and conviction rates.³⁵ As Berk puts it, “where there is more contact, there is a greater chance of apprehensions.”³⁶ Algorithms are then trained on this data that shows essentially “more crime” in certain areas, with certain groups of people, etc., perpetuating statistical inaccuracies.³⁷ The tools are not able to see through biases because neither is that what they are trained to do, nor is the data used for input corrected for these prejudices.

Besides these biases, accuracy issues arise due to discrepancies between the intended purpose of the assessment tool and its actual implementation. As noted in *Loomis*, “the use of these tools at sentencing is more complex because the sentencing decision has multiple purposes, only some of which are related to recidivism reduction.”³⁸ Wisconsin selected COMPAS as the statewide tool for assisting correctional officers in assessing risk of pretrial release misconduct and recidivism, yet the courts there approved the tool’s

PROPUBLICA (May 23, 2016), <https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing>.

³³ Liu et al., *supra* note 28, at 132; Nicholas Scurich & John Monahan, *Evidence-Based Sentencing: Public Openness and Opposition to Using Gender, Age, and Race as Risk Factors for Recidivism*, 40 L. HUMAN BEHAVIOR 36, 37 (2016).

³⁴ Curtis, *supra* note 12, at 82.

³⁵ See Rachel K.E. Bellamy et al., (Tim Menzies ed.) *Think Your Artificial Intelligence Software is Fair? Think Again*, IEEE SOFTWARE: REDIRECTIONS, June 18, 2019, at 77, <https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=8738152&tag=1>; *Conference and Workshop Report on Assessing the Impact of Machine Intelligence on Human Behaviour: An Interdisciplinary Endeavour*, at 58-65, COM (Mar. 5-6, 2018) [hereinafter *Impact of Machine Intelligence*], <https://arxiv.org/pdf/1806.03192.pdf#page=60>; Frederick A. Miller et al., *AI x I = AI²: The OD Imperative to Add Inclusion to the Algorithms of Artificial Intelligence*, 50 OD PRACTITIONER 8 (2018), https://www.researchgate.net/profile/Roger_Gans2/publication/323830092_AI_x_I_AI2_The_OD_imperative_to_add_inclusion_to_the_algorithms_of_artificial_intelligence/links/5aad244e0f7e9b4897be932a/AI-x-I-AI2-The-OD-imperative-to-add-inclusion-to-the-algorithms-of-artificial-intelligence.pdf.

³⁶ BERK, *supra* note 10, at 118.

³⁷ See *Impact of Machine Intelligence*, *supra* note 35, at 59-60.

³⁸ *Loomis*, *supra* note 3, at ¶ 3.

assessment being considered at sentencing as well.³⁹ These are markedly different purposes.

On the other side, there have been numerous (more likely than not outweighing the negative claims) advancements in management of offenders by including algorithmic tools. For example, a study of machine learning forecasts and practices for the Pennsylvania Board of Probation and Parole, analyzing the incorporation of these forecasts in informing parole release decisions, concluded that, although the parole release rate stayed the same, there was an improvement in decisions made between violent and nonviolent offenders.⁴⁰ Scholars have advocated for the use of these actuarial methods over clinical judgment because of their efficiency, greater objectivity, and overall greater accuracy.⁴¹

PART III. MITIGATING FUTURE DOWNFALLS OF RISK ASSESSMENT

Despite the success stories of risk assessment algorithms, their ubiquitous use requires stricter analysis of the pits and downfalls they present or magnify. This part will look at some pressing questions that arise from the use of algorithmic risk assessment tools: What are the legal issues at bar? Why do we hold algorithmic decisions to a stricter standard than human judgment? What does a way forward look like?

A. *The constitutional questions and the legal fiction of an individualized assessment*

Up until now, there has been a host of legal issues facing the lower courts when determining the parameters and limitations of risk assessment tools in pretrial incarceration, and parole supervision and recidivism analysis. Like the issues facing the court in *Loomis*, there are questions about whether a system recommending incarceration pretrial violates due process, Equal Protection, or the Eighth Amendment (cruel and unusual punishment). Laws or action arguably violative of due process must have a compelling government interest as to why someone would be detained pretrial, and the public interest must outweigh the private harm.⁴² When it comes to the Equal Protection clause, the deprivation of liberty cannot, on its face, be discriminatory against immutable characteristics (gender, race, national origin). However, if a disparate impact is a result not directly influenced by these factors, who's to say it is discriminatory? As

³⁹ *Id.* at ¶¶ 37-38.

⁴⁰ See Berk, *supra* note 20, at 193-216.

⁴¹ See Lepri et al., *supra* note 32, at 612; Grant T. Harris et al., *VIOLENT OFFENDERS: APPRAISING AND MANAGING RISK* 195 (3d ed. 2015).

⁴² Dalakian, *supra* note 7, at 350.

previously mentioned, other factors can serve as proxies for race, namely zip code, socioeconomic status, and level of education, but there are arguments on both sides as to whether or not this concern is valid.⁴³

The Eighth Amendment proscribes cruel and unusual punishment, and the posting of excessive bail. Alarming, seventy percent of adults in local jails in 2017 at any given time were not convicted of any crime.⁴⁴ Pretrial detention can occur either because offenders are unable to post bail, or they have been determined to be a serious flight or violence risk to themselves or the community. There are no enumerations, at least federally speaking, about what constitutes excessive bail or whether a lengthy pretrial detention (as sometimes happens with the severe taxing of busy judicial systems) is considered “cruel and unusual.” This should be of concern to those in the legal field and more closely analyzed.

Loomis argued for the right to an individualized assessment—a part of Wisconsin’s criminal jurisprudence that varies state-to-state, and is not a federally mandated liberty. What is interesting about this argument in the context of a machine algorithm is that an offender will know no more about the individualized assessment of an algorithm than of a judge.⁴⁵ We do not know why humans make the decisions they do and yet their word—at least the judge’s—is law. Perhaps we hold machines to a higher standard because they are easier to correct than human thought: “[a]ctuarial risk assessments and judges alike render decisions based on a comparison to the average of their sample. . . . Both activities are prone to human error and inaccuracy, yet while one has more legitimacy in law today, the other is likely more correctable once errors are identified.”⁴⁶ Human judgment varies based on numerous external factors; we even see patterns that are non-existent as a means of justifying decisions.⁴⁷ Further, the taking into account of an algorithmic determination can, itself, affect judicial discretion—are there times when a “high risk” algorithmic label does not result in a longer sentence despite other factors?⁴⁸ When it comes to the weighing of quantitative factors of an algorithm against human logical or verbal reasoning, judges can also fall prey to automation bias—believing that an algorithmic assertion is methodically superior and, thus, definitively authoritative.⁴⁹

⁴³ See Liu et al., *supra* note 28, at 132. *But see* Dalakian, *supra* note 7, at 346.

⁴⁴ Dalakian, *supra* note 7, at 336-37.

⁴⁵ See *id.* at 347.

⁴⁶ *Id.* at 349.

⁴⁷ Curtis, *supra* note 12, at 14.

⁴⁸ Liu et al., *supra* note 28, at 130.

⁴⁹ Wisser, *supra* note 25, at 1824.

B. *Taking the offensive and paving the way forward*

Recognizing the systemic disadvantages society has placed on certain groups, particularly in the context of incarceration, is the first step. In order for these tools to be more successful and level the playing field, all stakeholders must acknowledge and aspire to eliminate discrimination in our culture. Understanding that algorithms have the ability to stop perpetuating racial and societal inequities is a way forward.⁵⁰ Implementing this solution can start with cohesive oversight across the board of these tools. Companies like IBM and Microsoft have undertaken fairness research in order to train artificial intelligence and machine learning algorithms to mitigate ingrained biases and discrimination.⁵¹ IBM's open source toolkits and code modules (AI Fairness 360) allow users to examine and make changes to biases or prejudices in assessment algorithms. For example, the "Reweighting" code can be used "to mitigate bias in training data" and it "[m]odifies the weights of different training examples."⁵²

New York state has enacted the first algorithmic accountability law as of January, 2018.⁵³ It allows for transparency and inquiry into the decision-making process by the public.⁵⁴ However, several arguments have been made in favor of banning proprietary tools, allowing only non-proprietary tools that permit open source viewing and oversight.⁵⁵ While this seems like a good idea, there are unexamined implications on corporate research and development of these very tools. Would it cause the creation of these genuinely efficient tools to come to a standstill? Others have called for governmental oversight by the Department of Justice or evaluation by independent scientific researchers.⁵⁶ The AI Now Institute released a report encouraging transparency of models and diversity of staff in testing and

⁵⁰ See Dalakian, *supra* note 7, at 351, 367-68; Miller et al., *supra* note 35, at 9. But see Joichi Ito, *AI Isn't a Crystal Ball, But It Might Be a Mirror*, WIRED—IDEAS (May 9, 2018, 8:00 AM), <https://www.wired.com/story/ideas-ai-as-mirror-not-crystal-ball/>.

⁵¹ Bellamy et al., *supra* note 35, at 78; Paul R. Daugherty et al., *Using Artificial Intelligence to Promote Diversity*, 60 MIT SLOAN MANAGEMENT REV., Winter 2019, <https://sloanreview.mit.edu/article/using-artificial-intelligence-to-promote-diversity/>. See also Matt Turek, *Explainable Artificial Intelligence*, DEFENSE ADVANCED RESEARCH PROJECTS AGENCY, <https://www.darpa.mil/program/explainable-artificial-intelligence> (last visited Aug. 5, 2019); DATA TRANSPARENCY LAB, <https://datatransparencylab.org> (last visited Aug. 5, 2019).

⁵² *AI Fairness 360 Open Source Toolkit*, IBM RESEARCH TRUSTED AI, <https://aif360.mybluemix.net> (last visited Aug. 5, 2019).

⁵³ Wisser, *supra* note 25, at 1825.

⁵⁴ *Id.*

⁵⁵ See Dalakian, *supra* note 7, at 344.

⁵⁶ Stephane Lacambra et al., *Recidivism Risk Assessments Won't Fix the Criminal Justice System*, ELECTRONIC FRONTIER FOUNDATION (December 21, 2018), <https://www.eff.org/deeplinks/2018/12/recidivism-risk-assessments-wont-fix-criminal-justice-system>.

developing the tools.⁵⁷ Berk distinguishes the three types of oversight strategies that can take place: pre-processing (removing sources of unfairness in the training data), in-processing (moderating the impact of the biased data), and post-processing (curbing unfairness in risks determined by algorithmic output).⁵⁸ The use of these oversight techniques can result in adjustments of how certain factors are weighed and bring to light how other inputs can serve as proxies for illegitimate factors like race.⁵⁹

The evaluation for accuracy and oversight, though, would mean little if the parameters, scope, and goals of the tool are not clearly defined. Violence prediction is not violence prevention, unless the risk is managed.⁶⁰ Stakeholders and users of these tools must explicitly delineate: What is the goal—is it preventing future crimes by offenders, mitigating others from committing crimes, rehabilitation, or punishment? What is meant by recidivism—is it committing a violent offense, a general offense, having an arrest, a conviction, or an incarceration? We are not predicting criminal behavior, but rather contact with the criminal justice system: “[a]n offender likely to be wrongly arrested, reconvicted, or reincarcerated will still be predicted to recidivate.”⁶¹ Further, users must consider in what context the tool is being applied. Sentencing and parole decisions are dramatically different and require distinctive inputs and weighing of factors.⁶² For example, young age can be indicative of imposing a shorter sentence as offenders tend to age out of crime, but when looking at pretrial incarceration, younger offenders are less likely to appear in court.⁶³

What may also help in the future in mitigating the issues with systemic social and algorithmic bias is to look at institutional fixes. Mental health issues like psychopathy and personality disorders are the biggest predictors of violent reoffense, but can be managed through social and academic programs.⁶⁴ Other illnesses can be treated and intervention can additionally help reduce incidents that these algorithms try to predict.

PART IV. CONCLUSION

Oversight and reforms are necessary to ensure unbiased algorithms can function in a biased society. Their incorrect use will lead

⁵⁷ Dalakian, *supra* note 7, at 344.

⁵⁸ BERK, *supra* note 10, at 125.

⁵⁹ *Id.* at 127.

⁶⁰ Viljoen et al., *supra* note 28, at 182.

⁶¹ Curtis, *supra* note 12, at 84.

⁶² BERK, *supra* note 10, at 18.

⁶³ Dalakian, *supra* note 7, at 364-65.

⁶⁴ Harris et al., *supra* note 41, at 236-38.

to expanding of the incarceration playing field, rather than a leveling of it, which only serves as a detriment to the country economically and socially. The core principle of “innocent until proven guilty” has become a muddled adage, superseded by over-incarceration until trial. Constitutional violations are teetering at a precipice. But, we can course correct by prioritizing transparency in the algorithm, oversight by independent groups, and clear definitions of the problems and goals being sought. However, all of this is meaningless if first we do not accept the fact that our society is biased with biased data. Only then, can we truly level the playing field for minorities, the mentally ill, and drug-addicted offenders.