QUANTIFYING CRIMINAL PROCEDURE: HOW TO UNLOCK THE POTENTIAL OF BIG DATA IN OUR CRIMINAL JUSTICE SYSTEM

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ABSTRACT

Big data's predictive algorithms have the potential to revolutionize the criminal justice system. They can make far more accurate determinations of reasonable suspicion and probable cause, thus increasing both the efficiency and the fairness of the system, since fewer innocent people will be stopped and searched.

However, three significant obstacles remain before the criminal justice system can formally use predictive algorithms to help make these determinations. First, we need to ensure that neither the algorithms nor the data used are based on improper factors, such as the race of the suspect. Second, under Fourth Amendment law, individualized suspicion is an essential element of reasonable suspicion or probable cause. This means that either the predictive algorithms must be designed to take individualized suspicion into account, or the predictive algorithms can only be used as one factor in determining whether the legal standard has been met, forcing police and judges to combine the algorithms' results with individualized factors. And finally, the legal standards themselves must be quantified so that police and judges can use the numerical predictions of big data in their reasonable suspicion and probable cause determinations.

These obstacles are not insurmountable. And if the necessary changes are made, the criminal justice system will become far more transparent, since the factors the algorithms take into consideration will necessarily be reviewable by judges and the general public

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alike. Furthermore, setting a quantified likelihood for reasonable suspicion and probable cause will allow us to engage in a healthy debate about what those numbers ought to be, and it will also ensure conformity across different jurisdictions.

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INTRODUCTION

The criminal justice system has always been concerned with predictions.[1] Police officers on patrol predict which suspects are

1. *See* BERNARD E. HARCOURT, AGAINST PREDICTION: PROFILING, POLICING, AND PUNISHING IN AN ACTUARIAL AGE 17-18 (2007) ("The truth is, most criminal justice determinations rest on probabilistic reasoning. The jury's verdict at trial, for instance, is nothing more than a probabilistic determination of prior fact. So is a police officer's determination whether there is sufficient cause to search or arrest a suspect; a judge's decision whether a suspect was coerced to confess; or even a forensic laboratory's conclusion regarding a DNA match—or DNA exoneration."). Professor Harcourt goes on to draw a sharp distinction between the

engaged in criminal activity in order to determine where to focus their investigative efforts. Magistrates deciding whether to grant a search warrant predict the odds that contraband will be found based on the facts presented in a warrant application. Judges conducting bail hearings predict the chances that a defendant will return to court for trial, and sentencing judges try to determine whether a convicted defendant is likely to reoffend if he is given a nonincarceration sentence.

Since the inception of our criminal justice system, law enforcement officers and judges have relied primarily on experience, training, intuition, and common sense in making their predictions.[2] In response, courts have crafted broad standards to accommodate these subjective judgments and allow for flexibility in application. For example, police officers may briefly detain an individual if they reasonably believe that "criminal activity may be afoot,"[3] while magistrates should issue a warrant if "a man of prudence and caution [believes] that the offense has been committed."[4]

The broad, flexible nature of these standards is no accident: They have been intentionally left imprecise by generations of courts. One reason is the nearly infinite number of different facts that could arise in any criminal case, which make hard and fast rules rather impractical.[5] But the main reason these rules have been kept

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necessary probabilistic decisions that are inherent in the criminal justice system and what he calls the "actuarial" determinations that are derived from "statistical correlations between group traits and group criminal offending rates," which should be avoided if at all possible. *Id.* at 18.

2. There were certainly scattered examples of statistical prediction instruments before the big data era. Statistical prediction methods were developed as early as 1935 to determine the likelihood of a prisoner's success if paroled; by the late twentieth century similar statistical prediction instruments were being used by dozens of states. *Id.* at 1, 7-9. Likewise, in the 1970s and 1980s federal Drug Enforcement Administration officers used "drug courier profiles" to determine which passengers at airports to investigate. *Id.* at 15-16. But the rise of big data, with its vast amounts of information and vastly powerful methods of processing that data, brings the promise (or the threat) of a true revolution in the sophistication and the proliferation of these tools.

3. Terry v. Ohio, 392 U.S. 1, 30 (1968).

4. Carroll v. United States, 267 U.S. 132, 161 (1925). Occasionally specific, recurring fact patterns lead to more specific applications of these rules: For example, police officers know that if they observe a suspect fleeing from them while in a high crime neighborhood, those two factors result in reasonable suspicion that the suspect has committed a crime. Illinois v. Wardlow, 528 U.S. 119, 124-25 (2000).

5. The Supreme Court has explained that "probable cause is a fluid concept—turning on the assessment of probabilities in particular factual contexts—

ambiguous is that police and courts have historically lacked the necessary tools to evaluate the accuracy of their predictions with any precision. Thus, state actors have been forced to rely on their own subjective beliefs and anecdotal evidence in making their predictions.[6]

All of that is now changing. Modern methods of data collection and analysis commonly known as "big data" are providing police and judges with tools that can predict future behavior with greater precision than ever before.[7] These tools hold out the promise of increased fairness and greater objectivity at many of the critical decision points in our criminal justice system. But despite the potential of big data tools, three significant obstacles potentially bar their effective incorporation into the criminal justice system.

First, we need to ensure that the tools of big data are not hard-wired to produce discriminatory results. If the predictive algorithms consider race or religion as a factor, then using these algorithms to predict behavior is unacceptable (and illegal) no matter how much they may increase accuracy. Similarly, if the algorithms themselves were developed based on past discriminatory practices, we need to develop new algorithms based on better data.

Second, Fourth Amendment law mandates that decisions to stop or search a suspect be based at least in part on individualized suspicion. Because big data involves processing large amounts of information, its algorithms frequently generate predictions based on broad generalizations rather than specific conduct. Thus, in their current form, these algorithms cannot on their own form the basis for reasonable suspicion or probable cause.

And finally, the current legal standards that govern police officers and judges are imprecise and subjective. Courts have deliberately created them to be imprecise and seem to have every intention of keeping them that way. Unfortunately, these nebulous standards are a poor fit for big data's highly precise and quantitative tools.

These obstacles are not insurmountable barriers. Big data algorithms can be structured so that they are truly race neutral and

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not readily, or even usefully, reduced to a neat set of legal rules." Illinois v. Gates, 462 U.S. 213, 232 (1983).

6. For example, a magistrate might reasonably conclude that a defendant who does not have a steady job seems less likely to come back to court on her own; furthermore, last month the magistrate remembers releasing a defendant who did not have a steady job and sure enough, she did not appear for her court date.

7. *See infra* Part I.

take into account individualized conduct when making their calculations. But in order to ensure that they meet these requirements, the factors they apply must be transparent to judges. In other words, it is not sufficient for reviewing courts to know that these algorithms are working; the courts must also understand exactly how the methods work to ensure that those methods meet the appropriate legal standards.[8] And although courts have historically been reluctant to attach specific numbers to the relevant legal standards, there is no doctrinal barrier to doing so. Courts may be more willing to take this step as they come to realize that big data offers highly precise and quantitative tools that can create not only better accuracy but also greater transparency in our criminal system.

This Article seeks to harmonize the analytical world of big data with the legal world of criminal justice. If those who design the big data tools can ensure the transparency of their algorithms and databases, not only will these tools become more palatable to the courts, but the transparency of these calculations will simultaneously improve the transparency of the criminal justice system. Moreover, if courts embrace the use of numerically quantifiable data, not only will we achieve greater accuracy in the administration of justice, but we will also achieve greater clarity of the process.

Part I of this Article discusses the ways in which big data can increase the accuracy of our criminal justice system.[9] Part II addresses the challenges involved in the use of big data.[10] Part III explains how these challenges can be overcome by requiring heightened transparency of big data's algorithms and databases and by introducing quantifiable standards into our criminal justice system.[11] The Article concludes by positing that big data tools, if properly designed and used, can dramatically improve both the accuracy and transparency of our criminal justice system.

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8. *See* Andrew Guthrie Ferguson, *Predictive Policing and Reasonable Suspicion*, 62 EMORY L.J. 259, 319-20 (2012). Unfortunately, as these algorithms become more accurate, they also become more complicated, and the databases they use become even larger and more detailed, making them less comprehensible to the average police officer or judge. We will consider this problem in more detail in Section III.A.

9. *See infra* Part I.

10. *See infra* Part II.

11. *See infra* Part III.

I. THE PROMISE OF BIG DATA: INCREASED ACCURACY

"Big data" is the practice of accumulating extraordinarily large amounts of information from a variety of different sources and then processing that information using statistical analysis.[12] The results of these analyses are termed "mechanical predictions" in contrast with subjective "clinical judgments," which are based on the individual decision-maker's past experience and knowledge.[13]

Private companies have been using big data for over a decade to predict consumer behavior. Retailers use it to determine and change shopping habits.[14] Insurance companies rely on big data to try to identify the safest drivers and healthiest people in their customer pool.[15] Banks and credit agencies use big data to determine the likelihood that a potential borrower is a credit risk.[16] And all sorts of companies buy and sell this data to each other, seeking to mine it for information about their customers that they can use for economic advantage.[17]

In the criminal law context, mechanical predictions can be used to assist decision-makers in making the judgment calls that are integral to the criminal justice system. The extraordinary promise of applying big data to the criminal justice system is based on two

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12. *See* Andrew Guthrie Ferguson, *Big Data and Predictive Reasonable Suspicion*, 163 U. PA. L. REV. 327, 352-53 (2015).

13. *See* William M. Grove et al., *Clinical Versus Mechanical Prediction: A Meta-Analysis*, 12 PSYCHOL. ASSESSMENT 19, 19 (2000).

14. A famous Forbes story reported that Target had used big data from seemingly random purchasing to determine that a minor customer was pregnant and then sent the customer coupons for pregnancy and new baby items before the teenager had notified her parents that she was pregnant. *See* Kashmir Hill, *How Target Figured Out a Teen Girl Was Pregnant Before Her Father Did,* FORBES (Feb. 16, 2012, 11:02 AM), http://www.forbes.com/sites/kashmirhill/2012/02/16/ how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/#3363735834c6 [https://perma.cc/BA2Q-8HK4].

15. *See* Brian Fung, *The Big Data of Bad Driving, and How Insurers Plan to Track Your Every Turn*, WASH. POST (Jan. 4, 2016), https://www.washingtonpost.com/news/the-switch/wp/2016/01/04/the-big-data-of-bad-driving-and-how-insurers-plan-to-track-your-every-turn/ [https://perma.cc/999Q-K9TZ].

16. *See* EVA WOLKOWITZ & SARAH PARKER, BIG DATA, BIG POTENTIAL: HARNESSING DATA TECHNOLOGY FOR THE UNDERSERVED MARKET 11 (2015), http://www.morganstanley.com/sustainableinvesting/pdf/Big_Data_Big_Potential.pdf [https://perma.cc/DY42-K2Q7].

17. *See* Meta S. Brown, *When and Where to Buy Consumer Data (and 12 Companies Who Sell It)*, FORBES (Sept. 30, 2015, 9:49 AM), http://www.forbes.com/sites/metabrown/2015/09/30/when-and-where-to-buy-consumer-data-and-12-companies-who-sell-it/#c8b7ed1711bc [https://perma.cc/NJN9-57LE].

aspects of these mechanical predictions. First, the underlying data is usually gathered from public sources, and therefore, the use of such data does not constitute a "search" under the Fourth Amendment.[18] Thus, law enforcement officers have a significant amount of freedom in acquiring this information, which means that they can obtain the predictions from big data without needing to meet any legal standard such as reasonable suspicion or probable cause. Essentially, big data algorithms can be seen as a force multiplier, allowing police to generate more predictive power from the same public information that has always been available to them.

The second enticing aspect of big data's mechanical predictions is that they are more accurate than clinical judgments. Studies have shown that big data's mechanical predictions are, on average, 10% more accurate than clinical predictions.[19] Police officers and judges who have adopted these methods have been seeing increased accuracy in many different contexts, ranging from predicting where crime is likely to occur to determining which defendants are most likely to succeed if released on parole.[20] The increased accuracy offered by big data will lead to both greater efficiency and fairness. The system will be more efficient because police and courts will be able to focus their resources more effectively. It will be fairer because innocent people will be less likely to be stopped, frisked, searched, or arrested if big data can successfully narrow the field of legitimate suspects.

Big data's predictive algorithms could be used in a number of different ways in the criminal justice system. First, law enforcement officers could use these tools to determine where crime is likely to occur and to allocate their resources accordingly; as we will see in Section I.A, police are already using big data tools for this purpose,

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18. Recently, there have been signs that the Fourth Amendment may be expanded so that the gathering or processing of massive amounts of public data may be considered a search. Although government surveillance of public places, or of publicly available sources, does not implicate the Fourth Amendment, *see, e.g.*, United States v. Knotts, 460 U.S. 276, 281-82 (1983), the Supreme Court has hinted at the possibility that gathering and processing large amounts of information from public sources to learn information about a suspect could implicate the Fourth Amendment through the "mosaic" theory, United States v. Jones, 132 S. Ct. 945, 954-55 (2012) (Sotomayor, J., concurring), but that doctrine has not yet gained widespread acceptance in courts. For an overview and a critique of the mosaic theory, see Orin S. Kerr, *The Mosaic Theory of the Fourth Amendment*, 111 MICH. L. REV. 311 (2012).

19. Grove et al., *supra* note 13, at 19.

20. *See infra* notes 22-27, 69-71 and accompanying text.

with notable success. Second, the results from these predictive algorithms could informally influence police officers when they make their clinical judgments about whether reasonable suspicion or probable cause exists; as I argue in Section I.B, this is probably already occurring. Third, police could formally cite the results from predictive algorithms in court when justifying their stops or searches or when applying for a search warrant. As we see in Section I.C, there is as yet no evidence that law enforcement has done this, although this is likely to happen soon. Finally, the results from big data's predictive algorithms could be outcome determinative, meaning that a police officer or a judge would only consider the algorithm's output and ignore all other evidence. We are a long way from this point in the context of reasonable suspicion or probable cause, but Section I.D notes that some courts are coming close to allowing mechanical predictions to be outcome determinative for bail, sentencing, and parole decisions.[21]

A. Predictive Algorithms and Policing

Police have a long history of using massive amounts of data to help decide where to deploy resources.[22] In the 1990s, law enforcement use of data compilation gained national attention with the New York Police Department's COMPSTAT program.[23] Crime mapping algorithms quickly spread to other cities and became a staple of big-city policing.[24] Today, more advanced software has

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21. There is likely to be enormous resistance to adopting a system that is outcome determinative in any of these contexts, though I will argue that such an option is preferable in certain contexts. *See infra* Section III.B.

22. For an excellent overview of the use of predictive algorithms by police officers, see Andrew Guthrie Ferguson, *Policing Predictive Policing*, 94 WASH. U. L. REV. (forthcoming 2017).

23. *See* Sewell Chan, *Why Did Crime Fall in New York City?*, N.Y. TIMES CITY ROOM (Aug. 13, 2007, 2:10 PM), http://cityroom.blogs.nytimes.com/2007/08/13/why-did-crime-fall-in-new-york-city/?_r=2 [https://perma.cc/2HS9-E27E].

24. In addition to New York, sophisticated crime-mapping software has been used in Los Angeles, St. Louis, Philadelphia, San Francisco, Washington, D.C., Oakland, and many other cities. *See* Stuart Wolpert, *Predictive Policing Substantially Reduces Crime in Los Angeles During Months-Long Test*, UCLA NEWSROOM (Oct. 7, 2015), http://newsroom.ucla.edu/releases/predictive-policing-substantially-reduces-crime-in-los-angeles-during-months-long-test [https://perma.cc/3PTX-JXK6]; Maurice Chammah, *Policing the Future*, VERGE (Feb. 3, 2016), http://www.theverge.com/2016/2/3/10895804/st-louis-police-hunchlab-predictive-policing-marshall-project [https://perma.cc/X7UZ-Y4XP]; Darwin Bond-Graham & Ali Winston, *All Tomorrow's Crimes: The Future of Policing Looks a Lot Like*

made crime-predicting software available in smaller jurisdictions, and the National Institute of Justice is funding research into the efficacy of such programs.[25]

These crime prediction software systems vary considerably in their sophistication. One program known as PredPol (short for "predictive policing") only looks at past reports of criminal activity and then highlights areas of the precinct in which crime has been most prevalent during specific time periods.[26] The police department then assigns more officers to the high-crime areas in order to detect or deter crime more effectively. Police officers using the software in a suburb of Los Angeles saw their crime rate decrease by 13% over the course of four months, while it rose by 0.4% in surrounding areas.[27] A more sophisticated program called HunchLab also uses reports of past criminal activity, but adds in additional factors.[28] Some of these extra factors, such as the proximity to subway stations or bars, or the current weather conditions, have an obvious correlation to particular types of criminal activity. Other factors seem unrelated, such as the decrease in aggravated assaults on windy days, or the increase in car thefts near schools.[29]

The Fresno Police Department uses crime prediction software in a somewhat different way, employing a software system called Beware to warn police officers of the threat level for the location of a

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Good Branding, SF WEEKLY (Oct. 30, 2013), http://www.sfweekly.com/sanfrancisco/all-tomorrows-crimes-the-future-of-policing-looks-a-lot-like-good-branding/Content?oid=2827968 [https://perma.cc/2ARE-MFS2]; Eugene K. Chow, *Is Predictive Policing Making* Minority Report *a Reality?*, WEEK (Oct. 7, 2013), http://theweek.com/articles/459396/predictive-policing-making-minority-report-reality [https://perma.cc/3X7W-R3VG]; Darwin Bond-Graham, *Oakland Mayor Schaaf and Police Seek Unproven 'Predictive Policing' Software*, E. BAY EXPRESS (June 24, 2015), http://www.eastbayexpress.com/oakland/oakland-mayor-schaaf-and-police-seek-unproven-predictive-policing-software/Content?oid=4362343 [https://perma.cc/99HG-MYPA].

25. *See* Chammah, *supra* note 24.

26. *Id.*; *see* Cameron Albert-Deitch, *Predictive Policing Crime Prevention Software Successful for APD*, ATLANTA MAGAZINE (Nov. 10, 2014), http://www.atlantamagazine.com/news-culture-articles/predictive-policing-crime-prevention-software-successful-for-apd/ [https://perma.cc/F8YY-2JRE]. PredPol is now being used by more than fifty different police agencies in the United States and Britain. *See* Chammah, *supra* note 24.

27. *See* Chammah, *supra* note 24. Other jurisdictions have seen similar improvements in crime rates: Norcross, Georgia, saw a 20% decrease in crime after adopting PredPol, which led the Atlanta police department to adopt it as well. *See* Albert-Deitch, *supra* note 26.

28. *See* Chammah, *supra* note 24.

29. *Id.*

911 call.[30] As law enforcement officers are on their way to the location, workers in police headquarters plug the address into the Beware program, which quickly analyzes countless pieces of data, including "arrest reports, . . . commercial databases, deep Web searches and . . . social media postings" that are associated with that address.[31] The program then offers a rating for the location: green for safe, yellow for caution, and red for dangerous.[32] Police officers who arrive at the scene can take appropriate precautions based on that rating.

Chicago takes this process one step further, using predictive software to determine which individuals are most likely to be involved in a crime.[33] Using a special algorithm designed by an engineer at the Illinois Institute of Technology, the Chicago Police Department created a "heat list" of 400 people who are "most likely to be involved in a shooting or homicide."[34] Police will then deploy resources to monitor these individuals more closely than other individuals[35] in an attempt to deter their criminal behavior by letting them know they are under increased surveillance or to swiftly apprehend them if they do commit crimes.[36]

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30. Justin Jouvenal, *The New Way Police Are Surveilling You: Calculating Your Threat 'Score'*, WASH. POST (Jan. 10, 2016), https://www.washingtonpost.com/local/public-safety/the-new-way-police-are-surveilling-you-calculating-your-threat-score/2016/01/10/e42bccac-8e15-11e5-baf4-bdf37355da0c_story.html [https://perma.cc/B5HT-PNT9].

31. *Id.*

32. *Id.*

33. Matt Stroud, *The Minority Report: Chicago's New Police Computer Predicts Crimes, But Is It Racist?*, VERGE (Feb. 19, 2014, 9:31 AM), http://www.theverge.com/2014/2/19/5419854/the-minority-report-this-computer-predicts-crime-but-is-it-racist [https://perma.cc/J6VQ-Q64E].

34. *Id.*; *see also* Robert L. Mitchell, *Predictive Policing Gets Personal*, COMPUTERWORLD (Oct. 24, 2013, 7:00 AM), http://www.computerworld.com/article/2486424/government-it/predictive-policing-gets- personal.html [https://perma.cc/6SR9-4QGW] (describing a similar program in North Carolina).

35. Stroud, *supra* note 33.

36. *Id.* Kansas City has been using a similar program, known as KC NoVA, which targets individuals "at risk" of committing violent crimes. The program warns these individuals that they are being watched and that "harsh penalties will be imposed for even petty slights once warnings have been given," but it also provides services such as housing and social services to help the individuals stay out of trouble. *See* John Eligon & Timothy Williams, *Police Program Aims to Pinpoint Those Most Likely to Commit Crimes*, N.Y. TIMES (Sept. 24, 2015), http://www.nytimes.com/2015/09/25/us/police-program-aims-to-pinpoint-those-most-likely-to-commit-crimes.html?_r=0 [https://perma.cc/7UYW-KFDM].

Using predictive software to determine how to allocate scarce law enforcement resources is not limited to investigations of street crime. The Internal Revenue Service (IRS) uses a secret algorithm to determine which of the over one hundred million tax returns should be audited each year. The IRS algorithm scans through every tax return, looking for outlying levels of deductions or other factors that indicate a higher chance of fraud, and then it assigns a risk level to each return.[37] Those returns with high risk factors are then personally reviewed by IRS agents to see if an audit is appropriate.[38]

Some critics of adapting big data to our criminal justice system argue that it does not, in fact, make more accurate decisions. Professor Bernard Harcourt has argued that predictive policing may actually reduce the efficiency of stops and searches, because when police focus their resources on certain portions of the population, they necessarily withdraw resources from other portions of the population.[39] According to his model, crime will decrease among those who are targeted, but it will increase among those who are not targeted; thus, whether the overall crime rate decreases actually depends on the comparative elasticity of the crime rate in each of the two groups.[40] This critique is persuasive if the police are using a very basic predictive policing model that focuses on one specific neighborhood or (as in Harcourt's example) one specific race. But the critique becomes weaker if the police are using a multi-factor algorithm to direct resources, and it becomes weaker still if it is merely used to determine whether reasonable suspicion or probable cause exist. However, Harcourt's objection does highlight the need to ensure that the data used by the predictive algorithm remains current; that is, if there is a feedback effect that makes certain factors less likely to indicate criminal activity, the algorithm should be adjusted to ensure that those factors are given less weight or eliminated entirely. It also highlights a legitimate concern about relying on data which itself may be tainted by past discrimination or inaccurate decisions, a topic we will address in Section III.A below.

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37. *See* HARCOURT, *supra* note 1, at 10.
38. *Id.*
39. *Id.* ch. 4.
40. *Id.* at 123.

B. Predictive Algorithms as Background Data

PredPol, Hunchlab, Beware, Chicago's "heat list," and the IRS algorithm represent what we could call the first stage of crime prediction algorithms—algorithms used to help police decide where and how to deploy their resources, but not used (at least formally) to make any specific legal determination.[41] But as the amount of data about individuals grows and becomes more accessible, police will use big data at later stages of the criminal justice system. It is likely that police already informally use these tools as background information in making their determination as to whether reasonable suspicion or probable cause exists.

Assume a police officer observes marginally suspicious activity—say, a suspect walking slowly down the street at night, peering into windows and constantly looking over his shoulder. If the officer is using crime prediction software, and the software informs her that she is currently in a low crime neighborhood with few burglaries, she may simply assume that the suspect is engaged in innocent conduct and merely observe the suspect for a few minutes until he leaves the area. But if the software informs her that there are many burglaries that occur in this neighborhood at this time of night, that extra factor could be enough to change her response and lead her to conduct a *Terry* stop of the suspect. Or consider a police officer who uses risk assessment software and shows up at a home in response to a 911 call to find two individuals engaged in a heated argument, one with a bruise on his cheek. The injured individual refuses to tell the police officer whether he has been assaulted. If the risk assessment software flashes a peaceful green, the responding officer might simply give a warning to the two individuals or ask one of them to take a walk to cool down. But if the software presented a red light, indicating the presence of a violent individual at the location, the officer might decide that she has probable cause to arrest the uninjured individual and charge him with assault.

The same calculus would occur—consciously or unconsciously—when an officer is investigating a potential crime and a member of a heat list is a suspect, or when an IRS agent is reviewing a return that has already been flagged by the software. Other police officers have mobile applications that can display the

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41. Another example of law enforcement using big data to try to detect criminal activity is the National Security Agency's massive metadata collection program. *See* ACLU v. Clapper, 785 F.3d 787, 792, 816-17 (2d Cir. 2015).

location of individuals suspected of gang activity, registered sex offenders, or those who have outstanding warrants, thus allowing a police officer to quickly generate reasonable suspicion or probable cause.[42] Indeed, presence in a "high crime area" is a factor that is frequently cited by police officers who are explaining why they believed that reasonable suspicion existed,[43] and the fact that a suspect is a known violent felon could also be used by an officer in deciding whether to make an arrest.[44] Many law enforcement agents (and many lay people) would say that it would be foolish to ignore these signals when deciding on the appropriate course of action.

Although police probably use these results as background information in making their determination, so far no law enforcement agent or prosecutor has formally used the results of crime prediction software in court as a factor to support reasonable suspicion or probable cause.[45] Instead, courts rely on the testimony of the law enforcement officers to establish the necessary factors, even in situations where big data could provide more accurate information.[46]

C. Predictive Algorithms as Formal Factors

The increasing pervasiveness of predictive algorithms in policing means that police officers will soon be using these predictions as part of their arguments justifying reasonable suspicion or probable cause. Moreover, as police officers use these factors

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42. *See* Ferguson, *supra* note 12, at 368-69.

43. *See, e.g.*, Illinois v. Wardlow, 528 U.S. 119, 124 (2000).

44. *See, e.g.*, State v. Carter, 697 N.W.2d 199, 205 (Minn. 2005).

45. A recent comprehensive report from the RAND Corporation surveyed every known use of predictive algorithms in law enforcement and showed no evidence of such algorithms being used to determine reasonable suspicion or probable cause. *See* WALTER L. PERRY ET AL., RAND CORP., PREDICTIVE POLICING: THE ROLE OF CRIME FORECASTING IN LAW ENFORCEMENT OPERATIONS 107-08 (2013).

46. For example, in the *Wardlow* case, the Court merely accepted the testimony of the officer that the stop occurred in an "area known for heavy narcotics trafficking." 528 U.S. at 119-23. In fact, the actual crime data from the Chicago district where the stop occurred showed that the district ranked just at the median for criminal activity of the twenty-five districts in the city. *See* Amici Curiae Brief of the National Ass'n of Police Organizations et al. in Support of Petitioner at 7, *Wardlow*, 528 U.S. 119 (No. 98-1036), 1999 WL 451226, at *7. For an excellent discussion of how crime mapping has been used (or ignored) by the Supreme Court, see Andrew Guthrie Ferguson, *Crime Mapping and the Fourth Amendment: Redrawing "High-Crime Areas"*, 63 HASTINGS L.J. 179 (2011).

more often, judges will begin to expect this kind of hard data and may begin to reject the current subjective, experiential, or anecdotal evidence that officers currently rely upon.[47] This will almost certainly result in more accurate determinations overall. To see why, we need to take a closer look at the current system that is used to determine reasonable suspicion or probable cause.

For example, consider the "high-crime area" determination that is frequently cited by police officers as a factor supporting reasonable suspicion or probable cause. The opinion of a police officer about how much crime occurs in a certain area is likely to be based on a small sample of cases; it may be based on an outdated reputation of a neighborhood; and it is possibly tainted by many different kinds of bias.[48] Even if accurate, it is inappropriately comparative. If the neighborhood in question has three times the number of drug arrests per week than all of the surrounding neighborhoods, that fact in itself is irrelevant to a reasonable suspicion argument.[49] Instead, the police officer and the judge should consider the absolute number of criminal activity—does the neighborhood in question have two drug arrests per week, or ten drug arrests per week, or fifty drug arrests per week?[50]

Take another example: An officer is only allowed to frisk a suspect during a *Terry* stop if the officer has a reason to believe the suspect is armed. Up until now, that "reason to believe"—like the reasonable suspicion underlying the stop itself—has been based on the opinion and past experience of the police officer and evaluated based on the intuition of the reviewing court. Police officers

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47. Ferguson, *supra* note 46, at 221-22 ("If the officer did not base his decision on specific data about a specific crime problem in a specific area, or if the data relied upon did not demonstrate a specific and relevant crime problem, then reliance on this information should not be considered.").

48. *Id.* at 224-25. Professor Ferguson notes that using actual data about high-crime areas will probably be an improvement: "While not perfect, a more data-driven approach is an improvement over the police 'war stories' that have essentially served as the basis of prior designations of high-crime areas. In fact, analysis of crime data has shown that subjective opinions about high-crime areas are often erroneous." For a discussion of the possible inherent biases in the data, see *infra* Subsection II.A.2.

49. Ferguson, *supra* note 46, at 223.

50. In fact, the best numbers to consider would not be based on arrest, but rather on actual criminal activity. Using arrest numbers as a proxy for criminal activity may lead to a number of inaccuracies, which I discuss in Section III.B, *infra*. For a good discussion on the difficulty of determining whether a neighborhood is a "high-crime area" in the absence of any evidence from big data, see United States v. Wright, 485 F.3d 45, 49-50 (1st Cir. 2007).

routinely testify, for example, that individuals suspected of engaging in narcotics transactions are more likely to have weapons on their person. In practice, judges have credited this testimony, regularly approving *Terry* frisks when the police officer had reasonable grounds to believe a suspect was engaged in narcotics trafficking.[51] But what is the actual link between selling narcotics and weapons possession? If the former actually does make the latter more likely, what is the degree of increase in probability? Is it the same for every city, and every neighborhood of every city, and every type of narcotic? Clinical judgments can answer none of these questions—nor can they answer these questions for any other factor relied upon by police when justifying a *Terry* frisk. Thus, the "reason to believe" standard has become a legal term of art, defined not by actual probability but by years of precedents in which certain fact patterns have been approved by courts based solely on the experience and expertise of police officers.

In fact, the Bureau of Justice review of over 200,000 criminals who were convicted in state court shows that only 8.6% of those who were convicted of drug dealing carried a firearm at the time of the offense, and only 7.8% of those convicted of drug possession carried a firearm at the time of the offense.[52] Does an 8.6% chance give officers a "reason to believe?" Judges have never answered this question, preferring instead to rely on the self-reported intuition and experience of the very police officers who are trying to justify their own actions.

Other used factors for clinical judgments also may comport with the intuition of police officers (and with the intuition of the judges who review the police officers' actions), but may be empirically false. For example, flight from police has long been held to be a significant factor in determining reasonable suspicion,[53] but studies have shown that in "high-crime urban communities where the

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51. *See, e.g.*, *Wardlow*, 528 U.S. at 122 ("[Officer Nolan] immediately conducted a protective patdown search for weapons because in his experience it was common for there to be weapons in the near vicinity of narcotics transactions.").

52. CAROLINE WOLF HARLOW, BUREAU OF JUSTICE STATISTICS, FIREARM USE BY OFFENDERS 3 (2001). The report also found that 2.9% of those who committed sexual assault carried a firearm, while 4% of those who committed burglary carried a firearm. *Id.* Of course, the *Terry* standard asks courts to consider the likelihood that the suspect has a weapon, not merely a firearm, but this only emphasizes the need to apply more accurate statistics to the analysis.

53. *Wardlow*, 528 U.S. at 125; United States v. Dykes, 406 F.3d 717, 720 (D.C. Cir. 2005) (suspect was stopped in an area "known for the sales of cocaine and marijuana" and he fled upon seeing the officers exit their cars).

population is disproportionately minority," there is a very weak link between flight from police and criminal activity.[54]

Courts have long been criticized for deferring to the various factors police officers use in determining that they have the authority to make a *Terry* stop. In his dissent in *United States v. Sokolow*, Justice Thurgood Marshall listed dozens of cases in which different circuit courts had approved of contradictory factors offered to show that a suspect fit a "drug courier profile" at an airport: first to deplane; last to deplane, deplaned in the middle, one way ticket, round-trip ticket, nonstop flight, changed planes, gym bag, new suitcase, traveled alone, traveled with companion, acted nervously, acted too calmly.[55] As one pair of commentators noted, "Apparently almost any human trait can be a basis for suspicion, and nearly everybody exhibits several potentially suspicious . . . factors at any given time."[56]

In the recent case of *Floyd v. City of New York*,[57] a class action suit challenging the stop-and-frisk policies of the New York Police Department, the trial judge criticized the often used police factors such as "furtive movements," "high crime area," and "suspicious bulge" as overly vague.[58] During testimony in the case, two police

54. Tracey L. Meares & Bernard E. Harcourt, *Foreword: Transparent Adjudication and Social Science Research in Constitutional Criminal Procedure*, 90 J. CRIM. L. & CRIMINOLOGY 733, 792 (2000).

55. United States v. Sokolow, 490 U.S. 1, 13-14 (1989) (Marshall, J., dissenting). Illegal immigration profiles came under a similar attack in a dissent in *United States v. Zapata-Ibarra*, 223 F.3d 281, 281-82 (5th Cir. 2000) (Wiener, J., dissenting).

56. Samuel R. Gross & Katherine Y. Barnes, *Road Work: Racial Profiling and Drug Interdiction on the Highway*, 101 MICH. L. REV. 651, 740 (2002); *see also* Charles L. Becton, *The Drug Courier Profile: "All Seems Infected That Th' Infected Spy, As All Looks Yellow to the Jaundic'd Eye"*, 65 N.C. L. REV. 417 (1987); United States v. Broomfield, 417 F.3d 654, 655 (7th Cir. 2005) ("Whether you stand still or move, drive above, below, or at the speed limit, you will be described by the police as acting suspiciously should they wish to stop or arrest you. Such subjective, promiscuous appeals to an ineffable intuition should not be credited."); Utah v. Strieff, 136 S. Ct. 2056, 2069 (2016) (Sotomayor, J., dissenting) ("[An officer's] justification must provide specific reasons why the officer suspected you were breaking the law, but it may factor in your ethnicity, where you live, what you were wearing, and how you behaved. The officer does not even need to know which law you might have broken so long as he can later point to any possible infraction—even one that is minor, unrelated, or ambiguous." (citations omitted)).

57. 959 F. Supp. 2d 540 (S.D.N.Y. 2013).

58. *Id.* at 559-60. In the data from New York City reviewed by the court, "furtive movements" was cited as a factor 42% of the time; "high crime area" 55%

officers testified as to what they understood "furtive movements" to mean:

> One [officer] explained that "furtive movement is a very broad concept," and could include a person "changing direction," "walking in a certain way," "[a]cting a little suspicious," "making a movement that is not regular," being "very fidgety," "going in and out of his pocket," "going in and out of a location," "looking back and forth constantly," "looking over their shoulder," "adjusting their hip or their belt," "moving in and out of a car too quickly," "[t]urning a part of their body away from you," "[g]rabbing at a certain pocket or something at their waist," "getting a little nervous, maybe shaking," and "*stutter[ing]*." Another officer explained that "usually" a furtive movement is someone "hanging out in front of [a] building, sitting on the benches or something like that" and then making a "quick movement," such as "bending down and quickly standing back up," "going inside the lobby . . . and then quickly coming back out," or "all of a sudden becom[ing] very nervous, very aware."[59]

In the statistics from the *Floyd* case, police officers cited "furtive movements" as a factor in 42% of their stops.[60]

Not only are many of the clinical judgment factors overly vague, their supposed link to criminal activity is based on a very limited data set. Factors offered by law enforcement officers are frequently supported only by the officer's own prior experience, and in approving (or disapproving)[61] of these factors as probative of criminal activity, courts either cite the expertise of the officers or use their own intuition to evaluate the probability that a crime will occur.

Unsurprisingly, the result of these vague standards and limited data sets is a troublingly low hit rate for police officers conducting stop and frisks. The recent expansion of *Terry* stops in New York

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of the time, and "suspicious bulge" 10% of the time. *Id.* at 559. Sometimes the only factors cited by the officer were two of these three factors. *Id.*

59. *Id.* at 561. The officers in New York are hardly unique in their use of vague factors. In Philadelphia, police were engaging in overly aggressive *Terry* stops using factors such as "loitering" or "acting suspiciously"; after the police were sued over their tactics, they agreed in a consent decree to stop using these factors. *See* Plaintiffs' Fifth Report to Court and Monitor on Stop and Frisk Practices at 2-4, Bailey v. City of Philadelphia (E.D. Pa. 2013) (No. 10-5952).

60. *Floyd*, 959 F. Supp. 2d at 559.

61. In the *Sokolow* case itself, the Ninth Circuit held that there was no reasonable suspicion because the factors used by the agents were "vague and inchoate," "hazy in form, susceptible to great adaptations, and almost entirely speculative," and that "[t]he obvious lack of substantiation [of the government's conclusion] betrays its lack of merit." United States v. Sokolow, 831 F.2d 1413, 1423-24 (9th Cir. 1987). But seven Supreme Court Justices looked at the same factors and concluded that probable cause did exist. United States v. Sokolow, 490 U.S. 1, 9 (1989).

City resulted in a regime in which only 12% of all *Terry* stops in New York City resulted in an arrest or a summons.[62] During that same period, only 1.5% of the *Terry* frisks produced evidence of a weapon.[63] Thus, for that time period, the police officers' standard for reasonable suspicion was in fact a 12% likelihood that criminal activity was occurring, while their standard for a "reason to believe" that a suspect was armed (thus justifying a frisk) was 1.5%. Although courts have been unwilling to explicitly quantify the percentage chance for "reasonable suspicion," it is probably more than 12% and certainly more than 1.5%.[64]

Indeed, the district court in the Floyd case concluded that many of the stops by the police officers during this time period were not supported by reasonable suspicion.[65] This implies that the 12% success rate over that time period was insufficient to support reasonable suspicion, since it was the result of overly aggressive police tactics and the use of improper factors. Similarly, a review of police tactics in Philadelphia concluded that only 3% of the stops resulted in recovery of contraband; the review also concluded that reasonable suspicion was lacking for somewhere between 35% and 50% of these stops.[66]

Thus, there is a growing dissonance between the objective, data-driven tools used by police officers to guide their conduct, and the intuitive arguments and subjective experience used by police officers to justify that conduct in court. Given the success of the data-driven tools in everyday police work, it seems inevitable that they will soon be formally used by police officers in assessing whether reasonable suspicion or probable cause exists.

Although these predictive algorithms have not yet been used in the context of reasonable suspicion or probable cause, they are not

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62. *Floyd*, 959 F. Supp. 2d at 558.

63. *Id.*

64. *See infra* notes 241-250 and accompanying text for some estimates of where courts might set this number if predictive algorithms force them to do so.

65. For example, in 36% of the cases the police did not identify any suspected crimes and approximately half the forms used "Furtive Movements" and "High Crime Area" as factors, which the judge determined were "vague and subjective terms" that cannot on their own "reliably demonstrate individualized reasonable suspicion." *Floyd*, 959 F. Supp. 2d at 559-60.

66. *See* Plaintiffs' Fifth Report, *supra* note 59, at 3-4. The police conceded that the rate of stops without documented reasonable suspicion was around 35%, but argued that this high number was due to "incomplete paperwork, improper narratives used by police officers, and an overall lack of credibility in the electronic data base." *Id.* at 4.

completely foreign to the criminal justice system. As we will see in the next Section, courts have been using these predictive algorithms in other contexts, such as bail hearings and parole hearings.

D. Predictive Algorithms Elsewhere in the Criminal Justice System

The final step in the use of predictive algorithms is for the police officers and judges to make their decisions based solely on the outputs of the algorithms without exercising any of their own independent judgment. We may never get to this stage for reasonable suspicion and probable cause determinations (and we may not want to, as discussed below),[67] but we have come close to such a world in other contexts, such as bail determinations, sentencing decisions, and parole judgments. For decades, judges used generalizations based on risk factors in making these decisions, but in recent years, just as in the policing context, big data has slowly been infiltrating these procedures, using vast quantities of data to empirically test traditional factors and experiment with new factors.[68]

One example of this shift in the bail context is the Public Safety Assessment (PSA) designed by the Arnold Foundation, which has been adopted by about two dozen jurisdictions over the past few years.[69] The PSA, which is based on an analysis of one and a half million criminal cases, uses up to ten different objective factors to determine whether a defendant is a flight risk or likely to commit a crime during pretrial release.[70] The results of the PSA have been nearly uniformly positive—after pilot projects, the city of Charlotte lowered its pretrial detention by 20%, with no increase in crime or

67. *See infra* notes 265-282 and accompanying text.

68. In particular, the empirical scholarship on this issue has grown to focus on big data techniques such as machine learning or massive statistical analyses. *See, e.g.*, Richard A. Berk, Susan B. Sorenson & Geoffrey Barnes, *Forecasting Domestic Violence: A Machine Learning Approach to Help Inform Arraignment Decisions*, 13 J. EMPIRICAL LEGAL STUD. 94 (2016); Richard Berk & Jordan Hyatt, *Machine Learning Forecasts of Risk to Inform Sentencing Decisions*, 27 FED. SENT'G REP. 222 (2015); Richard A. Berk & Justin Bleich, *Statistical Procedures for Forecasting Criminal Behavior: A Comparative Assessment*, 12 CRIMINOLOGY & PUB. POL'Y 513 (2013).

69. Shaila Dewan, *Judges Replacing Conjecture with Formula for Bail*, N.Y. TIMES (June 26, 2015), http://www.nytimes.com/2015/06/27/us/turning-the-granting-of-bail-into-a-science.html?_r=0 [https://perma.cc/P8NE-LDUL].

70. *Id.*

bench warrants, while the state of Kentucky has saved significant money and increased accuracy of its pretrial decisions.[71]

The sentencing process is also undergoing a quiet revolution in the methods that judges use to assess risk of reoffending. Some states now use formal "risk assessment instruments" to determine the appropriate sentence after conviction.[72] These risk assessment instruments are designed using an algorithm that takes into account decades of prior cases.[73] They typically use around ten different inputs, such as age and history of alcohol abuse, and then assign defendants a number on a scale, which translates to a percentage chance that the defendant will reoffend within a certain period of time.[74] For example, Virginia developed a nine-factor risk assessment instrument based on past evidence and uses the instrument to help determine whether to divert a defendant away from a prison sentence.[75] As of now, judges use these risk assessment instruments as tools to help them make their decision, and judges still maintain the discretion to depart from the recommendations made by the instrument,[76] but the influence of these instruments on the actual sentencing decision is growing.

Predictive algorithms have also gained popularity in assessing the appropriateness of parole. Mechanical predictions were used as far back as the 1920s, long before computers and large databases became available.[77] The goal of these early predictions was to assess an inmate's risk of recidivism. Due to the vast number of individuals who were paroled, even in the early years there was a large pool of subjects for a natural experiment. Sociologists and psychologists utilized this pool to examine the characteristics of those who did and did not succeed on parole.[78] By 2004, over 70% of states that maintained an active parole system employed some form of mechanical predictive instrument in determining whether parole was

71. *Id.*

72. Christopher Slobogin, *Risk Assessment*, in THE OXFORD HANDBOOK OF SENTENCING AND CORRECTIONS 196, 203-05 (Joan Petersilia & Kevin R. Reitz eds., 2012).

73. *Id.* at 200.

74. *Id.* at 204.

75. *Id.* The risk assessment tool looks at type of offense, gender, age, employment status, and four aspects of the defendant's criminal record. *Id.*

76. *Id.* For example, in Virginia, 59% of defendants who were considered to be a low risk by the algorithm were still sentenced to a prison term by the judge. *Id.*

77. *See* HARCOURT, *supra* note 1, at 48-51.

78. *Id.* at 48.

appropriate.[79] One common tool, the Level of Services Inventory-Revised (LSI-R), takes into account fifty-four separate factors ranging from criminal history and education level to alcohol abuse and attitude towards sentencing.[80] Courts, correctional facilities, and parole boards routinely use these instruments in determining what level of supervision an inmate needs in prison, whether he should be paroled, and what conditions are necessary if parole is granted.[81]

Like police officers, judges who make clinical judgments about bail, sentencing, or parole may subconsciously or explicitly use stereotypes or intuitions that are incorrect.[82] In creating the PSA, the Arnold Foundation determined that many traditional factors used in bail hearings, such as defendant's employment status, community ties, or drug and alcohol abuse, were poor predictors of flight risk.[83] They also concluded that a face-to-face interview—traditionally a staple of prearraignment assessment—was not a useful tool.[84] In the sentencing context, many judges had long believed that mental illness was a strong indicator of recidivism; actual studies of mentally ill criminals have shown that not to be the case.[85]

There are two obvious differences between the predictive algorithms used by police during their investigations and those used by courts in making decisions about bail, sentencing, or parole. The first seems significant but in fact is relatively trivial: The police officers are making predictions about past or current behavior (i.e., whether the person they are about to stop is currently engaged in criminal activity or whether the house they would like to search currently contains drugs), while courts are making predictions about future behavior (i.e., whether the defendant will return to court if released or whether the defendant will commit more crimes if released on parole). In truth, however, there is no material difference between these two types of predictions—both involve a decision-maker in the criminal justice system trying to use known facts to

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79. *Id.* at 78.
80. *Id.* at 80-81.
81. *Id.* at 82.
82. *Id.* at 20-21.
83. *Id.*; *see* Dewan, *supra* note 69.
84. HARCOURT, *supra* note 1, at 82; *see* Dewan, *supra* note 69.
85. Henry J. Steadman, *Implications from the Baxstrom Experience*, 1 J. AM. ACAD. PSYCHIATRY L. 189, 190, 193 (1973). Studies of nearly 1,000 inmates at a mental hospital for the criminally insane showed that over 97% of the inmate–patients did not return after being released; even among those with the highest risk factors (violent criminal history, juvenile record, numerous prior conviction), less than 10% returned. *Id.*

determine the odds that an unknown fact is true. As noted by Professor Barbara Underwood in one of the first articles regarding prediction and the law, "Some past or present facts are as elusive as any prediction, and some predictions can be made with as much confidence as most determinations of past fact."[86]

The second, more significant distinction is in the amount of time available to conduct the prediction. Police officers deciding whether to stop or arrest an individual on the street are reacting to an ongoing and sometimes rapidly changing situation, and therefore may not have the time to do anything but rely on their clinical judgments. Even if an accurate, fast-processing algorithm is available to the police, they may not have time to make the necessary observations that are required for the algorithm to deliver an accurate prediction. Judges who are reviewing these judgments at a later suppression hearing, as well as judges who are making decisions about search warrants, bail, sentencing, or parole, have the time to gather more data about the defendant and his circumstances, and then make use of a predictive algorithm in making their decision. In other words, predictive software may be less accurate when used by law enforcement officers than when used by judges.

Nevertheless, the success of these mechanical predictions in the context of bail and parole hearings shows that courts may be receptive to applying these tools on the front end of the criminal justice system—to justify stops, arrests, and searches. Data-driven predictive algorithms represent an opportunity to dramatically increase the accuracy of these decisions, thus ensuring that fewer innocent citizens are detained or searched, and increasing the efficiency of our law enforcement resources.[87] However, a number of obstacles remain—both in the design of the algorithms and in the legal standards used by courts. We will discuss these obstacles in the next Part.

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86. Barbara D. Underwood, *Law and the Crystal Ball: Predicting Behavior with Statistical Inference and Individualized Judgment*, 88 YALE L.J. 1408, 1413 (1979). Professor Underwood gives an example that "past states of mind are notoriously difficult to determine, and it is relatively easy to determine the amount of interest that will be paid by a bank on a deposit." *Id.* at 1413 n.10.

87. Bennett Capers, *Policing, Technology, and Doctrinal Assists*, FLA. L. REV. (forthcoming 2016) (manuscript at 33-38), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2760388 [https://perma.cc/NV47-URGD]; *see also infra* note 140-141 and accompanying text.

II. CHALLENGES TO USING PREDICTIVE ALGORITHMS

As noted in Part I, crime prediction software could soon be used by police officers on the street and by judges in criminal courts to prove reasonable suspicion or probable cause. This development could potentially result in more accurate and consistent determinations of whether these standards have indeed been met—but only if certain obstacles can be overcome. First, there is a concern that predictive algorithms would use factors that are illegal for courts to consider, such as the race of the subject.[88] Similarly, the underlying data that the algorithms use may be in itself biased; thus, using these algorithms would not actually increase accuracy but merely reinforce decades of discriminatory policing. Also, the law requires police officers and judges to act on facts that are specific to the case at hand; the general probability factors used by big data may not be able to provide this specificity. And finally, the hyper-quantified world of big data is currently an uncomfortable fit with the flexible standards used by courts.

All of these obstacles are surmountable, but only if the algorithms and databases used by the big data analyses are made more transparent so that courts can evaluate the underlying processes and the standards being used, and only if courts are willing to accept the quantified world of predictive software.

A. Detecting the Racial Biases in the Predictive Algorithms

To the extent that human beings have a hand in creating the algorithms and compiling the data that the algorithms use, human biases will infect the results. Although it is impossible to eliminate these biases altogether, there are ways to minimize the problems they create.

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88. Some scholars argue that many of the risk prediction factors currently in use in sentencing decisions may be unconstitutional because they rely directly or indirectly on race or other suspect classes. *See, e.g.*, Sonja B. Starr, *Evidence-Based Sentencing and the Scientific Rationalization of Discrimination*, 66 STAN. L. REV. 803, 819 (2014). *But see* Christopher Slobogin, *Risk Assessment and Risk Management in Juvenile Justice*, 27 CRIM. JUST. 10, 13-15 (2013) (use of gender and age in sentencing decisions is permissible because it survives intermediate scrutiny); J.C. Oleson, *Risk in Sentencing: Constitutionally Suspect Variables and Evidence-Based Sentencing*, 64 SMU L. REV. 1329, 1385-88 (2001) (sentencing factors survive a strict scrutiny analysis).

1. *Direct and Indirect Use of Forbidden Factors*

Mechanical predictions are not necessarily color-blind. If an individual's race is a significant factor in determining whether a certain outcome is likely to occur, then the individuals who are designing (and using) the algorithm may be tempted to use race as one of the inputs in order to achieve more accurate results. In some cases outside the context of criminal procedure, this may be relatively harmless—for example, when companies use big data to decide where to market certain products or when political campaigns use big data to decide which voters to contact with a certain kind of outreach. In other cases, race-based factors can be quite harmful (and illegal)—for example, in deciding which customers are a good credit risk for a home loan[89] or which job applicants should be hired.[90] In the context of criminal procedure, race-based factors are especially problematic, both legally and morally.

For the purposes of this discussion, let's assume that a private company has developed an algorithm that can predict with great accuracy whether drugs will be found inside a certain house. The algorithm requires the user to enter six different inputs, such as the neighborhood where the house is located, the prior criminal convictions of the house's owner, and observations made by police officers about activity outside the house. One of these inputs is the race of the owner of the home. Assume, further, that without using the race factor, the algorithm can predict the presence of drugs with 40% accuracy, but with the race factor, the algorithm can predict the presence of drugs with 55% accuracy. Assume the police have purchased this algorithm and are using it in their warrant application. Should they input the race factor in order to enhance the algorithm's accuracy? In other words, would it be illegal for the state to use race as a factor in determining probable cause or reasonable suspicion if it could be definitively proven that using race made the prediction more accurate?

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89. *See, e.g.*, Sarah Ludwig, *Credit Scores in America Perpetuate Racial Injustice. Here's How*, GUARDIAN (Oct. 13, 2015, 10:14 AM), https://www.theguardian.com/commentisfree/2015/oct/13/your-credit-score-is-racist-heres-why [https://perma.cc/4P6B-WM55]; 15 U.S.C. § 1691 (2012).

90. *See* Lee Price, *Racial Discrimination Continues to Play a Part in Hiring Decisions*, ECON. POL'Y INST. (Sept. 17, 2003), http://www.epi.org/publication/webfeatures_snapshots_archive_09172003/ [https://perma.cc/465W-KRGM]; 42 U.S.C. § 2000e-2 (2012).

Surprisingly, Fourth Amendment jurisprudence has little to say about whether race can be used as a factor in determining reasonable suspicion or probable cause. Courts are unanimous in holding that race alone can never be the basis for a stop or a search, for the obvious reason that a person's race alone can never create probable cause or even reasonable suspicion that criminal activity is occurring.[91] However, some courts have approved cases in which race was one of many factors in deciding whether reasonable suspicion or probable cause existed—for example, when searching for illegal immigrants near the Mexican border.[92] Other courts have disagreed, arguing that a person's race is "of such little probative value [in the reasonable suspicion analysis] that it may not be considered as a relevant factor."[93]

As these cases make clear, the only problem with using race under Fourth Amendment jurisprudence is that in the vast majority of cases, the race of a subject is not a relevant indicator as to whether the suspect is more or less likely to engage in criminal activity.[94] Therefore, any law enforcement official who does consider race is almost certainly doing so because of an irrational bias against that particular race. But this objection is not entirely valid in every circumstance—as noted above, if the law enforcement officer is looking for illegal immigrants near the Mexican border, for example, the suspect's race could conceivably be one factor in trying to predict whether the suspect was illegally in the country. Likewise, if a person seems "out of place" due to her race (for example, a white person in a predominantly black neighborhood), her race could be one factor that would lead to reasonable suspicion that she was engaging in criminal activity.[95]

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91. *See, e.g.*, United States v. Brignoni-Ponce, 422 U.S. 873, 886-87 (1975) ("[Mexican ancestry] alone . . . does not justify stopping all Mexican-Americans to ask if they are aliens.").

92. *Id.* ("The likelihood that any given person of Mexican ancestry is an alien is high enough to make Mexican appearance a relevant factor . . . ."); *see also* United States v. Martinez-Fuerte, 428 U.S. 543, 562-63 (1976).

93. United States v. Montero-Camargo, 208 F.3d 1122, 1135 (9th Cir. 2000).

94. *See, e.g.*, State v. Kuhn, 517 A.2d 162, 165 (N.J. Super. Ct. App. Div. 1986) ("No rational inference may be drawn from the race of [a person] that he may be engaged in criminal activities.").

95. It is harder to come up with an example in the bail context where the defendant's race was actually a relevant factor in determining flight risk or danger to the community. Certain factors that are correlated to race (such as income level or employment status) may be relevant, however.

Given this jurisprudence, there is no valid Fourth Amendment objection to using race as a factor in a mechanical prediction algorithm for reasonable suspicion or probable cause. Assuming we have a properly designed algorithm,[96] race would only be used as a factor if it actually was a useful predictor of individualized suspicion; in other words, there would be empirical statistical proof that in the given context race did help determine whether or not an individual was guilty of a crime.[97] In our hypothetical case, in which the use of race increased the accuracy of the prediction from 40% to 55%, using the race-based factor would not be prohibited under the Fourth Amendment.

The Equal Protection Clause is another matter, however. Under the Equal Protection Clause, race can only be used as a factor in state actions if the use of race is necessary and if it is narrowly tailored to achieve a compelling state interest.[98] This is a difficult, if not impossible, burden for law enforcement to meet in the stop-and-search context. Some courts have held that the use of race as a factor does not require exclusion as long as there were sufficient other factors to justify the stop or search,[99] while others have noted that law enforcement officers violate the Equal Protection Clause if they incorporate race routinely as a factor in their drug courier profile.[100] Neither of these principles bodes well for using race as a factor in mechanical prediction algorithms, regardless of how accurate it might be. As further evidence that racial factors are forbidden by the Equal Protection Clause, nearly all the civil suits alleging racial

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96. As we will see, one of the objections to using mechanical predictions is that the underlying data may be tainted by preexisting biases in the criminal justice system that overstate the criminal activity of certain ethnic minorities. *See infra* Subsection II.A.2.

97. *See, e.g.*, Whren v. United States, 517 U.S. 806, 813 (1996) ("[T]he constitutional basis for objecting to intentionally discriminatory application of laws is the Equal Protection Clause, not the Fourth Amendment."). *But see* Gross & Barnes, *supra* note 56, at 733-38 (surveying lower court decisions and concluding that "American judges are ambivalent and divided about the use of race as a basis for individualized suspicion under the Fourth Amendment. Lower court cases go both ways, but increasingly the tone is negative").

98. Adarand Constructors, Inc. v. Pena, 515 U.S. 200, 235 (1995).

99. *See, e.g.*, Lowery v. Commonwealth, 388 S.E.2d 265, 267 (Va. Ct. App. 1990).

100. *See, e.g.*, United States v. Taylor, 956 F.2d 572, 578-79 (6th Cir. 1992) (en banc); *see also* Tracey Maclin, *Race and the Fourth Amendment*, 51 VAND. L. REV. 333 (1998) (discussing the legality of racial profiling).

profiling result in consent decrees that forbid the use of race as a factor.[101]

Outside the Fourth Amendment context, the seminal case on racial bias in the criminal justice system is *McCleskey v. Kemp*, in which a black defendant argued that the state of Georgia engaged in racial discrimination when administering the death penalty.[102] The defendant relied on a study that showed that defendants who killed white victims were far more likely to be sentenced to death than those who killed black victims.[103] The study also showed that black defendants were more likely to get the death penalty than white defendants.[104] The Supreme Court rejected the defendant's arguments, holding that in order to prevail on an equal protection claim, the defendant had to demonstrate that the decision-makers in the process acted with a "discriminatory purpose."[105] The Justices were concerned with interfering with the discretion that is given to prosecutors, judges, and juries, and thus said it required "exceptionally clear proof before [the Court] would infer that the discretion has been abused."[106]

Based on this jurisprudence, it is hard to see our hypothetical algorithm passing constitutional muster. Even assuming that the interdiction of drugs is a compelling state interest, law enforcement would be hard pressed to argue that using the race-based factor was necessary and narrowly tailored to accomplish that purpose. The use of the algorithm would probably be seen as nothing more than a sophisticated method of racial profiling—an institutionalization of using race as a factor in determining probable cause.

The only plausible defense for the state would be to argue that although race is clearly a factor in the decision made by the algorithm, the decision is not made with a "discriminatory purpose" as forbidden by *McCleskey*. In other words, those who design and use the algorithm are (arguably) not acting with racial animus or out of any intent to treat the members of one race differently than another. This narrower definition of "discriminatory purpose" is consistent with *McCleskey*'s language, which held that

101. *See* Gross & Barnes, *supra* note 56, at 743 (citing settlement agreements with the Maryland State Police and various other Department of Justice racial profiling consent decrees).

102. 481 U.S. 279, 291-92 (1987).

103. *Id.* at 293-99 & n.11.

104. *Id.*

105. *Id.* at 292-93.

106. *Id.* at 297.

"'[d]iscriminatory purpose' . . . implies more than intent as volition or intent as awareness of consequences. It implies that the decisionmaker . . . selected or reaffirmed a particular course of action at least in part 'because of,' not merely 'in spite of,' its adverse effects upon an identifiable group."[107] This does not really fit the state's motivation in using the algorithm—the police are not choosing to use the algorithm (or, more specifically, the race factor) "because of" its adverse effects on a particular race; they are using it to increase the accuracy of their predictions.

However, the narrow definition of "discriminatory purpose" is not borne out in other areas of criminal procedure. For example, in the context of jury selection, the Court held that if a defendant established a pattern of racial discrimination in peremptory jury challenges, the prosecutor could only prevail if she could provide a racially neutral reason for making those challenges.[108] The Court further noted that "the prosecutor may not rebut the defendant's prima facie case of discrimination by stating merely that he challenged jurors of the defendant's race on the assumption—or his intuitive judgment—that they would be partial to the defendant because of their shared race."[109] This would be analogous to a prosecutor arguing that explicit discrimination should be allowed in the probable cause algorithm because it increases the accuracy of the prediction.

Thus, our hypothetical algorithm could not legally use race as a factor, however much that factor could be proven to increase accuracy. This legal conclusion is consistent with most individuals' intuitive moral sense and (relatedly) to the political feasibility of using predictive algorithms. In the past, the media has harshly criticized racial profiling,[110] and it is unlikely that the public would support a system that regularly and explicitly used race as a significant factor to determine whether to stop a person or search his home.

But explicit use of race is not the only potential problem in the context of predictive algorithms, and this is where the need for

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107. *Id.* at 298 (quoting Pers. Adm'r of Mass. v. Feeney, 442 U.S. 256, 279 (1979)).

108. Batson v. Kentucky, 476 U.S. 79, 97-98 (1986).

109. *Id.* at 97.

110. *See, e.g.*, Conor Friedersdorf, *The NYPD Officers Who See Racial Bias in the NYPD*, ATLANTIC (Jan. 7, 2015), http://www.theatlantic.com/national/archive/2015/01/the-nypd-officers-who-see-racial-bias-in-the-nypd/384106/ [https://perma.cc/3VS2-2X6F].

transparency becomes significant. It would be relatively easy for courts to enforce a rule that prohibits the police from using the defendant's race directly as a factor in predictive algorithms, but this may not prevent the algorithm from relying on factors that are strongly correlated to race. Assume we change our hypothetical algorithm and remove the race factor altogether, but still use the location of the house as one of the factors. As has been established by decades of redlining neighborhoods,[111] location can be an effective proxy for race in the context of providing insurance, banking services, health care, or many other types of services.[112] As we saw earlier, current software used by police to predict crime patterns is highly location-specific, and it is certainly possible to imagine a scenario in which higher-crime areas track the racial makeup of specific neighborhoods.[113] We can call this "indirect discrimination" as opposed to the unconstitutional direct discrimination that occurs when race is officially used as a factor.[114] Nearly every predictive program that is currently in use has given rise to concerns about indirect discrimination.[115] Thus, before law enforcement agents and judges officially use these programs to formally help them make their decisions, we need to determine whether it is legally or ethically permissible to use these nonracial elements that are correlated to race.

One way of answering this question is to note that proxies for race are already used in determinations of reasonable suspicion or

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111. The term "redlining" came from "residential security maps" that were used by the Federal Home Loan Bank Board ("FHLBB") in the 1930s to describe the quality of real estate investments in different parts of the city. Certain areas, known as "Type D" neighborhoods, were outlined in red on the map to indicate the riskiest areas for mortgages. *See* BRUCE SCHNEIER, DATA AND GOLIATH: THE HIDDEN BATTLES TO COLLECT YOUR DATA AND CONTROL YOUR WORLD 109 (2015).

112. *See id.*

113. *See supra* Section I.A.

114. The problem of indirect discrimination is related to a more sinister problem—that of intentional "masking." Masking occurs when a decision-maker truly wishes to discriminate, but knows that doing so explicitly is forbidden. The decision-maker then intentionally chooses factors that are close statistical proxies for race and then uses them as factors. *See, e.g.*, Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CAL. L. REV. 671, 692-93 (2016). Masking can occur when a decision-maker uses traditional clinical judgments as well when she uses mechanical predictions, but could be easier to achieve with big data methods. *Id.*

115. *See, e.g.*, Stroud, *supra* note 33; Julia Angwin et al., *Machine Bias*, PROPUBLICA (May 23, 2016), https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing [https://perma.cc/W6K7-XKME].

probable cause. Police officers routinely testify that they made their observations in a "high crime area" as a factor that led to their reasonable suspicion or probable cause.[116] No doubt in many instances, higher-crime neighborhoods will tend to be inner city neighborhoods with higher proportions of certain minority groups[117] (or at least this will be the perspective of many police officers and judges).[118]

And this formal use of proxies for race under the current system is likely only the tip of the iceberg. The unconscious (or conscious) racial biases of police officers and magistrates permeate every aspect of the front end of the criminal justice system.[119] Under the current system, police officers disproportionately stop and frisk black and Latino suspects, and they are more likely to engage in violent and even lethal conduct when interacting with these

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116. *See, e.g.*, Illinois v. Wardlow, 528 U.S. 119, 124 (2000).

117. *See* ELIZABETH KNEEBONE & STEVEN RAPHAEL, METRO. POLICY PROGRAM AT BROOKINGS, CITY AND SUBURBAN CRIME TRENDS IN METROPOLITAN AMERICA 2-3 (May 2011), https://gspp.berkeley.edu/assets/uploads/research/pdf/p66.pdf [https://perma.cc/EW7Z-UDMT].

118. Proxies for race are also used at other stages of the criminal justice system. At bail hearings, for example, magistrates will routinely consider the prior criminal history of the defendant in deciding whether the defendant is a flight risk or a danger to others. *See* DAVID N. ADAIR, JR., FED. JUDICIAL CTR., THE BAIL REFORM ACT OF 1984, at 6 (3d ed. 2006), http://www.fjc.gov/public/pdf.nsf/lookup/bailact3.pdf/$file/bailact3.pdf [https://perma.cc/N3TL-79JA]. Criminal history is linked to race because certain ethnic groups have higher rates of conviction than others. *See* George Gao, *Chart of the Week: The Black-White Gap in Incarceration Rates*, PEW RES. CTR. (July 18, 2014), http://www.pewresearch.org/fact-tank/2014/07/18/chart-of-the-week-the-black-white-gap-in-incarceration-rates/ [https://perma.cc/E45N-L6XQ]. Other factors that magistrates use, such as employment or home ownership, are strongly correlated to poverty, which is correlated to race. ADAIR, *supra*, at 6.

119. Of course, these biases permeate the rest of the criminal justice system as well, as evidenced by the statistics cited in *McCleskey v. Kemp*, 481 U.S. 227, 293-99 (1987), and other studies showing biases in prosecutorial charging decisions, jury verdicts, and sentencing. *See, e.g.*, Robert J. Smith & Justin D. Levinson, *The Impact of Implicit Racial Bias on the Exercise of Prosecutorial Discretion*, 35 SEATTLE U. L. REV. 795, 805-22 (2012) (bias in charging decisions); Robert Barnes, *Supreme Court to Hear Case of Alleged Racial Bias by Juror*, WASH. POST (Apr. 4, 2016), https://www.washingtonpost.com/politics/courts_law/supreme-court-to-hear-case-of-alleged-racial-bias-by-juror/2016/04/04/c9256e9c-fa92-11e5-9140-e61d062438bb_story.html [https://perma.cc/9Q2M-CW3T] (bias by jurors); Edward Helmore, *Racial Bias Evident in South Carolina Criminal Sentences, Study Reveals*, GUARDIAN (Feb. 29, 2016, 12:01 AM), https://www.theguardian.com/us-news/2016/feb/29/racial-bias-criminal-sentencing-south-carolina [https://perma.cc/2UFC-BLC2] (bias in sentencing). These biases, and ways in which to overcome them, are beyond the scope of this Article.

suspects.[120] The findings from the class action lawsuit challenging the expanded police stop and frisks in New York City[121] found that over an eight-and-a-half-year period, 52% of all the citizens subjected to *Terry* stops were black, even though black citizens made up only 23% of the population.[122] Studies have shown similar numbers in Philadelphia,[123] Los Angeles,[124] Boston,[125] and on the New Jersey turnpike.[126] Unlike the formal factors which can (at least in theory) be proven to be proxies for race, the use and effect of these informal decisions are difficult to detect and even more difficult to prove in court. These implicit biases on the part of police officers are also difficult to cure, even in the long run, since they exist in almost every individual, even those who harbor no conscious prejudices.[127]

In other words, the current system relies on personal, subjective clinical judgments that are based on some known factors (which are

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120. John Cassidy, *The Statistical Debate Behind the Stop-and-Frisk Verdict*, NEW YORKER (Aug. 13, 2013), http://www.newyorker.com/news/john-cassidy/the-statistical-debate-behind-the-stop-and-frisk-verdict [https://perma.cc/FT7P-QZTZ].

121. Floyd v. City of New York, 959 F. Supp. 2d 540, 556, 573-75 (2013).

122. *Id.* at 574. This disproportionality cannot be explained by a higher rate of criminal activity by black citizens, since the "hit rate" for stopping black citizens was actually lower than that for white citizens—1.0% of the frisks of black citizens resulted in a weapon and 1.8% resulted in contraband, while 1.4% of the frisks of whites resulted in a weapon and 2.3% resulted in contraband. *Id.*

123. *See* Plaintiffs' Third Report to Court and Monitor on Stop and Frisk Practices, Bailey v. City of Philadelphia (E.D. Pa. 2013) (No. 10-5952).

124. *See* IAN AYRES & JONATHAN BOROWSKY, A STUDY OF RACIALLY DISPARATE OUTCOMES IN THE LOS ANGELES POLICE DEPARTMENT (Oct. 2008), https://www.aclusocal.org/wp-content/uploads/2015/09/11837125-LAPD-Racial-Profiling-Report-ACLU.pdf [https://perma.cc/P9YV-9H2Y]. The report shows that black residents are three times as likely to be the subject of a *Terry* stop as white residents, but that black residents are less likely to receive a citation after the stop, demonstrating that "African Americans are more often subject to stops without justification where no ticket could be issued." ACLU OF S. CAL., RACIAL PROFILING AND THE LAPD: A SUMMARY OF PROFESSOR IAN AYERS' REPORT ON RACIALLY DISPARATE OUTCOMES IN THE LOS ANGELES POLICE DEPARTMENT, https://www.aclusocal.org/wp-content/uploads/2015/09/99227648-Racial-Profiling-the-LAPD.pdf [https://perma.cc/FHV5-4EQP].

125. *See* ACLU FOUND. OF MASS., BLACK, BROWN AND TARGETED: A REPORT ON BOSTON POLICE DEPARTMENT STREET ENCOUNTERS FROM 2007-2010 (Oct. 2014), http://www.bostonherald.com/sites/default/files/media/2014/10/08/black_brown_and_targeted_online.pdf [https://perma.cc/7VHB-Z5RH].

126. *See* John Lamberth, *Driving While Black: A Statistician Proves That Prejudice Still Rules the Road*, *in* RACE, ETHNICITY, AND POLICING: NEW AND ESSENTIAL READINGS 32, 33 (Stephen K. Rice & Michael D. White eds., 2010).

127. *See, e.g.*, Jerry Kang, *Trojan Horses of Race*, 118 HARV. L. REV. 1489, 1491-528 (2005).

explicitly described by the police officer or magistrate when requesting a warrant or justifying their decision) and some unknown factors (such as unconscious biases). Even for the explicitly listed known factors, the decision-makers do not (and likely could not) quantify the degree to which they relied on each individual factor.

For example, assume a police officer is driving through a neighborhood and notices a young black man standing on the street corner. The young man is dressed in a way that is common to the neighborhood but that the police officer identifies as consistent with gang affiliation. The man then looks over at the officer, immediately places something in his pocket, and then walks briskly away from the officer. Assume at this point the officer honestly believes that there is a reasonable suspicion that the man is engaging in criminal activity (that is, the officer is not out to hassle the young man and is not simply stopping people indiscriminately in the hope of finding contraband). The officer then gets out of her car and orders the man to stop.

Later on, the officer is required to justify her stop by explaining why she believed she had reasonable suspicion to believe criminal activity was afoot. She lists the following factors:

(1) The action took place in a high crime neighborhood;

(2) The suspect hid an item after noticing a police officer;

(3) The suspect attempted to leave the scene after noticing a police officer.

The police officer does not list (and may not even be consciously aware of) other factors that led her to believe the suspect may have been engaged in criminal activity:

(1) The suspect's race (the officer subconsciously believes that black men are more likely to possess guns or drugs than white men);

(2) The suspect's age (the officer believes that men in their twenties are more likely to be engaged in criminal activity than children or men over forty);

(3) The suspect's gender (the officer believes that men are more likely to be carrying drugs or weapons than women);

(4) The suspect's clothing (which is actually common to the neighborhood but which the police officer subconsciously associates with criminals);

(5) The way the suspect looked at the police officer, which the officer couldn't describe in testimony but which she associated with hostility to authority and to police specifically.

Racial bias played a role in the officer's determination that the defendant was likely engaged in criminal activity, but it is impossible to know to what degree. Of the formal elements, the fact that the encounter took place in a "high crime neighborhood" is likely correlated to race, but neither the officer nor the magistrate reviewing her conduct are able to explain exactly how important that factor was out of the three that were listed. And the fact that the suspect's race led the officer to focus on this particular individual (as opposed to the young white man she observed standing on a different street corner two minutes before this interaction) may have played a significant role in her decision or a very minor role. Likewise, the suspect's clothing (likely another proxy for race) may have been a strong motivator for her to act, or it may have been relatively insignificant. There is simply no way to measure, much less prove, the degree to which race or proxies for race influenced her decision to detain the suspect. Over the course of many years and tens of thousands of stops, a clear pattern will probably emerge that shows that this police department disproportionately stops people of color, but effective remedies at that point are hard to come by.

It is against this backdrop that we must evaluate any potential future use of predictive software. In contrast to the use of clinical judgments, predictive software will only base its results on the formal factors that are coded into its system. Thus, there will be no unconscious or hidden human biases that affect its decision. Furthermore, we can precisely quantify the degree to which each of the formal factors affects the result, so a judge (or a policymaker) can make an informed judgment as to whether certain factors that are proxies for race are dominating the calculation. In other words, under the current system of clinical judgments, the only way to infer indirect discrimination is by reviewing the aggregate results after many months or years have passed. Under a system of mechanical predictions, the level of indirect discrimination can be assessed even before a stop or a search occurs by examining the algorithm the police intend to use. Thus, the mechanical predictive algorithms can be designed to ignore (or at least minimize) improper factors such as race—something that may be impossible to do if we leave these determinations to the subjective determinations of police officers.[128]

All of this, however, depends on a high level of transparency in the algorithm itself, so that judges and other policymakers (including the police department that is considering adoption of the algorithm) can review the factors, their correlation (if any) to race, and the strength of any specific factor in reaching the result. We will

128. *See infra* Section III.A and accompanying text.

examine the challenges of achieving this level of transparency in Part III.

2. *Preexisting Biases in the Underlying Data*

A related concern about using mechanical predictions involves the underlying data that is used by the predictive algorithms. Put simply, if the underlying data is discriminatory, then the results that are based on that data will be discriminatory, and the supposedly color-blind algorithms will be doing nothing more than reinforcing the existing racial bias in the criminal justice system. In the civil context, commentators are beginning to pay close attention to these potential problems, noting that "[i]f a sample includes a disproportionate representation of a particular class . . . the results of an analysis of that sample may skew in favor of or against the over- or underrepresented class."[129]

As an example, assume that for the past twenty years a metropolitan police department has been disproportionately stopping, searching, and arresting black and Latino citizens. This disproportionate treatment does not stem from the fact that citizens from these groups are more likely to commit crimes, but from inherent racial biases in the criminal justice system, such as the tendency of police to engage with minorities more than with whites and the increased level of policing in minority neighborhoods.[130] Assume also that these stops, searches, and arrests result in conviction at a higher rate than stops, searches, and arrests of white citizens—again, not because the police are better at predicting crime for the minority citizens, but because of downstream biases in the criminal justice system: Because black and Latino defendants tend to be poorer,[131] they are less likely to be able to afford private lawyers

129. *See* Barocas & Selbst, *supra* note 114, at 686.

130. This is, of course, not really a hypothetical case. Studies have shown, for example, that black citizens are nearly four times as likely to be arrested on charges of marijuana possession as white citizens, even though both blacks and whites use the drug at similar rates. In some states, black citizens were eight times as likely to be arrested. Ian Urbina, *Blacks Are Singled Out for Marijuana Arrests, Federal Data Suggests*, N.Y. TIMES (June 3, 2013), http://nyti.ms/18KaQO5 [https://perma.cc/K5XQ-VMJ6]. One of the reasons for this disparity is that "police departments, partly driven by a desire to increase their drug arrest statistics, can concentrate on minority or poorer neighborhoods to meet numerical goals." *Id.*

131. *See, e.g.*, Suzanne Macartney, Alemayehu Bishaw, and Kayla Fontenot, POVERTY RATES FOR SELECTED DETAILED RACE AND HISPANIC GROUPS BY STATE AND PLACE: 2007–2011 at 1, American Community Survey Survey Briefs, United

and less likely to be able to afford bail; and because of conscious or subconscious prejudice on the part of prosecutors and judges, black and Latino defendants are more likely to be overcharged[132] (leading to higher rates of plea bargaining) and more likely to be convicted by a jury if the case goes to trial.[133]

These discriminatory stops, searches, arrests, and convictions will become the underlying data for the city's predictive algorithms, and they create two distinct problems for mechanical predictions. The first is related to the disproportionately high rate of encounters between the police and members of the minority community—the so-called "hassle" rate.[134] This will create large amounts of data about certain individuals or areas of a city and disproportionately small amounts of data about other individuals or areas. Thus, when an algorithm determines whether a neighborhood is a "high crime area," it will have a skewed interpretation of the frequency of crimes in different areas. This in turn will lead to more frequent searches of individuals in the "high crime areas," which will create a self-fulfilling prophecy as more individuals are stopped, searched, arrested, and thus convicted in those areas. Likewise, if an individual is determined to be at "high risk" for committing a crime, it could merely be reflecting the prejudices of police officers who have had previous encounters with the individual.[135] Professor Bernard Harcourt refers to this as the "ratchet" effect: If certain factors are already perceived as leading to higher levels of criminal activity, a

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States Census Bureau (February 2013) (showing black and Latino poverty rates at twice those for white Americans), http://www.census.gov/prod/2013pubs/acsbr11-17.pdf [https://perma.cc/X3YX-VJ6Y].

132. *Id.* at 10-12; *see also* RAM SUBRAMANIAN ET AL., VERA INST. OF JUSTICE, INCARCERATION'S FRONT DOOR: THE MISUSE OF JAILS IN AMERICA 15 (Feb. 2015), http://www.safetyandjusticechallenge.org/wp-content/uploads/2015/01/incarcerations-front-door-report.pdf [https://perma.cc/GRV7-NFRG].

133. SENTENCING PROJECT, REPORT OF THE SENTENCING PROJECT TO THE UNITED NATIONS HUMAN RIGHTS COMMITTEE: REGARDING RACIAL DISPARITIES IN THE UNITED STATES CRIMINAL JUSTICE SYSTEM 10-12 (Aug. 2013), http://sentencingproject.org/wp-content/uploads/2015/12/Race-and-Justice-Shadow-Report-ICCPR.pdf [https://perma.cc/NR9M-3ZDJ].

134. *See* Jane Bambauer, *Hassle*, 113 MICH. L. REV. 461, 464-65 (2015) (arguing that the "hassle rate"—the rate at which individuals are stopped by the police—is at least as important as the "hit rate"—the rate at which these encounters uncover criminal activity—because a low hassle rate will ensure that the police have particularized suspicion when they conduct their stops). We will discuss the problem of particularized suspicion in Subsection III.B.2, *infra*.

135. *See generally* Wayne A. Logan & Andrew Guthrie Ferguson, *Policing Criminal Justice Data*, 101 MINN. L. REV. 541 (2016).

predictive algorithm will lead police and judges to conduct and authorize more searches on suspects who meet these factors, leading to more arrests that are linked to those factors.[136]

The second problem relates to the disproportionately high ratio of convictions to arrests for minority populations—what is usually referred to as the "hit" rate.[137] The primary way to know whether a stop, search, or arrest is successful (is a "hit") is by examining conviction rates. Thus, even if in fact the police do find contraband at the same rate for every ethnic group that is searched, if certain minority groups are convicted at a higher rate after the contraband is discovered, the statistics will indicate a higher hit rate for those minority groups than for others. In other words, because these citizens are unfairly convicted at a higher rate, the stops and searches that are conducted against them will appear to be more effective.[138]

As with the decision-making process itself, this problem is not new to mechanical predictions. The "data" that are used by police officers and judges today—their own personal experiences—is similarly flawed.[139] The danger in moving towards a big data analysis in this context is not that a new problem will be created, but that—despite big data's promise of being color-blind and objective—the old problems will persist. Even worse, these old problems will become institutionalized and thus be even harder to successfully challenge and expose because they are presented as part of the "hard science" of big data.

These problems with underlying data are not insoluble. The issue is common to many uses of big data, and it arises when statistics that are kept for one purpose are used for another.[140] Stop-and-frisk statistics and criminal conviction numbers are not recorded for the purposes of sophisticated statistical study; thus, those who collect them generally make no effort to correct for any biases inherent in the process.[141] Part of the solution thus involves correcting the data—that is, estimating the rate of over-

136. *See* HARCOURT, *supra* note 1, at 145-71.

137. *Id.* at 112.

138. *See* Stroud, *supra* note 33 (discussing Chicago's "heat list" and noting that "[f]rom what the CPD is willing to share, most of the collected information for the heat list is focused on rap sheets—arrest and conviction records. So rather than collecting information on everyone, they're collecting and using information on people who have had interactions with the police").

139. *See* Bambauer, *supra* note 134, at 473-74.

140. *See* Barocas & Selbst, *supra* note 114, at 686 ("Data gathered for routine business purposes tend to lack the rigor of social scientific data collection.").

141. *See id.* at 674.

representation of minorities in the hassle rates and hit rates and then adjusting the numbers accordingly.[142] Another solution would be to use data from different sources, not just from information that results from police–citizen encounters. For example, algorithms could draw their underlying data from the Bureau of Justice Statistics' National Crime Victimization Survey,[143] which tracks crimes based on victim reports, as opposed to the more traditional method of tracking crime through police reports.[144]

Once again, these solutions require real transparency as to the data being used. Courts and policymakers need to demand to see the source of the data used by the predictive algorithms and need to be given the tools to evaluate whether the data is representative of reality or the product of discriminatory decisions or unfair processes from the past.

B. Ensuring the Computer Looks for Individualized Suspicion

Individualized suspicion is a bedrock requirement of almost any police action that implicates the Fourth Amendment.[145] If police officers knew that statistically speaking, 60% of everyone living in a certain building were guilty of possessing drugs, they would not be allowed to arrest everyone in the building, even though they would almost certainly have probable cause to believe that each person is guilty.[146] The Fourth Amendment demands a certain level of

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142. *Id.* at 727.

143. *See Data Collection: National Crime Victimization Survey*, BUREAU JUST. STAT., https://www.bjs.gov/index.cfm?ty=dcdetail&iid=245 [https://perma.cc/2DRN-VM9W] (last visited Nov. 19, 2016).

144. *See, e.g.*, *Uniform Crime Reporting*, FBI, https://www.fbi.gov/about-us/cjis/ucr/ucr#cius [https://perma.cc/46T7-XPCE] (last visited Nov. 19, 2016).

145. *See, e.g.*, Ybarra v. Illinois, 444 U.S. 85, 91 (1979); Maryland v. Pringle, 540 U.S. 366, 371 (2003); United States v. Cortez, 449 U.S. 411, 418 (1981). The only exception involves special needs searches, when police officers are (at least in theory) acting for a purpose other than crime control and are therefore permitted to conduct reasonable searches on defined groups of people (such as airline travelers, drivers, or students) in order to further that purpose. *See, e.g.*, Mich. Dep't of State Police v. Sitz, 496 U.S. 444, 449-50 (1990).

146. For a detailed discussion of the individualization requirement, see Bambauer, *supra* note 134, at 490-94. Bambauer begins with a variation on this hypothetical, in which the police obtain results of a study that shows that 60% of all Harvard dorm rooms contain illegal drugs. *Id.* at 462. This is adopted from a hypothetical proposed by Professor Orin Kerr. *See* Orin Kerr, *Why Courts Should Not Quantify Probable Cause*, *in* THE POLITICAL HEART OF CRIMINAL PROCEDURE 135-37 (Michael Klarman, David Skeel & Carol Steiker eds., 2012).

particularity; that is, not merely a statistical likelihood that a suspect is guilty based on his membership in a certain group, but a reference to particular characteristics or actions by the suspect that shows that he specifically is likely to be guilty.[147]

One objection to using mechanical predictions is that they will dilute or even eliminate the individualization requirement by focusing on broad categories instead of the individual's particularized conduct.[148] Even if big data's mechanical predictions could lead to more accurate results, it would be legally and morally wrong to punish a person based on membership in a specific group (such as economic class or age) instead of focusing on the person's individual actions.[149]

In order to address this concern, we first have to define what we mean when we say that suspicion must be individualized.[150] In general, we mean that police officers must look at the specific characteristics and actions of the suspect himself, and not determine reasonable suspicion or probable cause merely because the suspect is a member of a certain group. However, individualized suspicion does not preclude inferring facts about an individual based on his

147. *See* Arnold H. Loewy, *Rethinking Search and Seizure in a Post-9/11 World*, 80 MISS. L.J. 1507, 1518 (2011) (arguing that "demographic probabilities" are insufficient to create probable cause or reasonable suspicion; the police must also notice something "specific to the defendant to create the probability as to him").

148. *See, e.g.*, Underwood, *supra* note 86, at 1425-29; Michael L. Rich, *Machine Learning, Automated Suspicion Algorithms, and the Fourth Amendment*, 164 U. PA. L. REV. 871, 896-901 (2016). In fact, many of the objections to using statistical information in the criminal investigation process focus only on the requirement for individualized suspicion. *See* Erica Goldberg, *Getting Beyond Intuition in the Probable Cause Inquiry*, 17 LEWIS & CLARK L. REV. 789, 806-07 (2013).

149. *See, e.g.*, HARCOURT, *supra* note 1, at 173-92.

150. *See* Bambauer, *supra* note 134, at 469. Professor Bambauer examines (and rejects) four different conceptions of individualized suspicion: the need for case-by-case assessment, the need to engage in human intuition, the need to focus on conduct under the control of the suspect, and tracing suspicion from a crime to a suspect instead of from an individual to a crime. *Id.* at 469-82. She then proposes her own definition of individualization, which focuses on the "hassle rate"—that is, the proportion of the innocent population who were searched. *Id.* at 482-94. Using big data algorithms to determine reasonable suspicion or probable cause is not compatible with all of these definitions—for example, it downplays or eliminates the use of human intuition and will frequently start with an analysis of a suspect rather than with a crime. But these algorithms will be particularly useful if one adopts Professor Bambauer's concept of hassle rates, since they focus on specific hit rates and miss rates that can easily be quantified and included in a crime prediction algorithm.

membership in a certain group; it simply requires the presence of additional factors that are specific to the suspect. Even in the analog world of clinical judgments, police officers and judges routinely rely on assumptions about an individual based in part on the characteristics of their group. For example, police officers will give some weight to a suspect's known gang affiliation, while magistrates making bail determinations will consider whether a defendant is unemployed or has a criminal record.

However, it would be inappropriate to stop, search, or arrest an individual solely based on his membership in a specific group.[151] This would essentially be saying that the group characteristics of the individual are so suspicious that at any given moment there is reason to believe that he is likely to be engaging in criminal activity. In order to avoid this problem, courts have held that the police officer must observe conduct that gives her some reason to believe that the suspect is currently engaging in criminal activity.[152] These actions may be legal (but suspicious) conduct, such as running from the police, exiting a location where drugs are known to be sold while sticking something in a pocket, or wearing a heavy coat on a summer day. Or they may be legal and innocuous conduct, such as purchasing a one-way ticket or traveling with no luggage. But the reasonable suspicion or probable cause cannot be based only on who the person is; it must also be based on what the person does.[153]

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151. That is, it would be inappropriate to do so outside the context of a special needs search. *See supra* note 145.

152. *See* Terry v. Ohio, 392 U.S. 1, 30 (1968).

153. *See* Ferguson, *supra* note 12, at 388. Big Data Professor Ferguson further argues that there needs to be a link between the suspect's suspicious background information and his current actions: "Courts analyzing big data suspicion should thus be careful to require a direct link between the past data about a suspect and the observed suspicion." *Id.* Otherwise, Professor Ferguson argues that the background information is irrelevant to the reasonable suspicion analysis. *Id.* It is not clear how "direct" the link would have to be; however, many different types of criminal activity may be linked together in an officer's mind (such as prior convictions of illegal weapons possession combined with a current observation indicating possible drug dealing). *Id.* The linkage could be even more indirect—and yet statistically significant—when big data is used. For example, assume that a statistical analysis of thousands of burglars shows that individuals who have prior convictions for child abuse are 35% more likely to commit burglary than those without such a conviction. Even though there is no logical link between the two crimes, this fact could be considered as one factor (among many others) by an algorithm determining whether probable cause exists to believe a specific suspect is guilty of burglary.

The Supreme Court has repeatedly reminded us of the need to consider the specific actions of the individual being searched. In *Ybarra v. Illinois*, law enforcement officers with a warrant to search a tavern decided to stop and frisk every individual inside the tavern, under the theory that mere presence in a tavern where drugs were being sold generated reasonable suspicion that a person possessed drugs.[154] The Supreme Court rejected this argument, explaining that "the *Terry* exception does not permit a frisk for weapons on less than reasonable belief or suspicion directed at the person to be frisked."[155]

A mechanical prediction that is used to demonstrate reasonable suspicion or probable cause must meet these same criteria.[156] Law school hypotheticals aside, it is hard to imagine a situation in the real world where group characteristics alone rise to the level of reasonable suspicion, but it is theoretically possible that a mechanical prediction would arrive at such a result. Thus, any predictive software used to calculate whether reasonable suspicion or probable cause exists must require the observing officer to input the specific actions of the suspect as well as his general characteristics. The software would thus use these specific actions as part of its analysis, and it would be designed in such a way that it could not find reasonable suspicion or probable cause—regardless of the percentage chance of criminal activity occurring—unless the specific actions were a significant factor in the determination.[157]

C. Changing the Legal Standards

So far in evaluating the obstacles to adapting big data to criminal law, we have looked at the potential problems with the underlying data or the methods used to process that data. In other words, we have been concerned with shaping the way that mechanical predictions are made in order to ensure that they are consistent with the requirements of our criminal procedure jurisprudence. But even if these problems are solved, we face a potentially even greater obstacle: reshaping the criminal procedure jurisprudence so that it can use the information provided by big data.

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154. 444 U.S. 85, 87-89 (1979).

155. *Id.* at 94; *see also* United States v. Cortez, 449 U.S. 411, 418 (1981) ("[T]he process . . . must raise a suspicion that the particular individual being stopped is engaged in wrongdoing.").

156. *See* Ferguson, *supra* note 12, at 387-88.

157. If the software does not consider individualized suspicion, then police and judges must use it only as a factor in their analysis. *See infra* notes 276-282.

Simply stated, the quantitative results from mechanical predictions are incompatible with the broad, flexible standards used by police and judges in the world of criminal procedure.[158] Reasonable suspicion and probable cause are standards that have been intentionally kept vague by the courts. The Supreme Court has long resisted setting specific probabilities for the flexible concepts of reasonable suspicion or probable cause,[159] explaining that it is a "practical, nontechnical conception" which is "incapable of precise definition or quantification into percentages."[160] The Court explains to us that the concepts are not "readily, or even usefully, reduced to a neat set of legal rules"[161] and then follows through on this promise by providing a multitude of messy rules for police and lower courts to follow. Probable cause is defined as evidence that would "warrant a man of prudence and caution in believing that the offense has been committed" or as a "reasonable ground to believe that the accused [is] guilty."[162] Reasonable suspicion is defined as "obviously less demanding than . . . probable cause,"[163] requiring merely "some minimal level of objective justification."[164]

These definitions are rather unhelpful in providing guidance or clarity as to when a stop or a search is appropriate. No lay person would possibly know what these terms mean in the real world; police officers and law students must study dozens of fact patterns from case law to get a sense of what kinds of factors will create reasonable suspicion or probable cause. Forty-five years ago, one law professor surveyed 166 federal judges to ask them to quantify the concept of

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158. *See, e.g.*, Illinois v. Gates, 462 U.S. 213, 232 (1983) (describing probable cause as a "fluid concept . . . not readily, or even usefully, reduced to a neat set of legal rules").

159. *See, e.g.*, United States v. Sokolow, 490 U.S. 1, 7-8 (1989) ("We think the Court of Appeals' effort to refine and elaborate the requirements of 'reasonable suspicion' in this case creates unnecessary difficulty in dealing with one of the relatively simple concepts embodied in the Fourth Amendment. In evaluating the validity of a stop such as this, we must consider 'the totality of the circumstances—the whole picture.'" (quoting *Cortez*, 449 U.S. at 417)); *Gates*, 462 U.S. at 232 (describing probable cause as a "fluid concept").

160. Maryland v. Pringle, 540 U.S. 366, 370-71 (2003).

161. *Sokolow*, 490 U.S. at 7.

162. Carroll v. United States, 267 U.S. 132, 161 (1925). In another case, the Court noted that probable cause "deal[s] with probabilities. These are not technical; they are the factual and practical considerations of everyday life on which reasonable and prudent men, not legal technicians, act." Brinegar v. United States, 338 U.S. 160, 175 (1949).

163. *Sokolow*, 490 U.S. at 7.

164. INS v. Delgado, 466 U.S. 210, 217 (1984).

probable cause, and the results ranged from ten percent to ninety percent.[165] The same group of judges was asked to quantify the concept of reasonable suspicion, and most judges gave responses between ten percent and sixty percent.[166]

This imprecision has its costs: It creates inconsistency from jurisdiction to jurisdiction and even from judge to judge and it makes it harder for police to know whether their actions are legal at the time they take those actions.[167] It also forces magistrates and judges to rely on the subjective descriptions and personal judgments of the police officers, since these vague standards breed vague descriptions to meet those standards, such as "high crime neighborhood," "acting nervous," and "suspicious hand movements." Police officers who testify to these factors are usually not acting in bad faith; they are merely trying to find ways to satisfy an ambiguous legal standard. Perhaps worst of all, the imprecise standards make it difficult to evaluate the constitutionality of law enforcement actions on a larger scale. Assume that a study of all probable-cause-based automobile searches in a jurisdiction demonstrated that 32% of the time, the police found contraband. Does this mean that the police in this jurisdiction are following the law or that they are violating people's rights? Without any quantification of the standard, it is impossible to tell.

To some extent, the imprecision of these terms was a necessary evil. If the Supreme Court had instructed police that they needed to be at least 20% certain of an individual's guilt before conducting a

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165. C.M.A. McCauliff, *Burdens of Proof: Degrees of Belief, Quanta of Evidence, or Constitutional Guarantees?*, 35 VAND. L. REV. 1293, 1327 (1982). The vast majority of the judges were between the 30% and 60% range—16% answered 30%, 27% answered 40%, 31% answered 50%, and 15% answered 60%—still indicating a wide range of disagreements. *Id.*

166. *Id.* at 1327-28. Although a few outlying judges (somewhat inexplicably) answered 0% or 100%, the vast majority of judges were within the 10% to 60% range: 15% answered 10%, 20% answered 20%, 30% answered 30%, 13% answered 40%, 14% answered 50%, and 5% answered 60%. *Id.* The study also shows that the definition of probable cause is not just vague but also likely misleading: It purports to require evidence sufficient to support a belief that an offense has been committed, which would seem to mean that it is more likely than not that an offense has been committed. *Id.* at 1327. However, the average probability from the judges was 44.5%—below the "more likely than not" standard. *Id.* at 1332. The First Circuit agreed with this formulation, holding that probable cause was a lower standard than preponderance of the evidence. United States v. Melvin, 596 F.2d 492, 495 (1st Cir. 1979). In other words, "probable cause" does not actually mean "probable"; it means something that is close to probable. *See infra* notes 242-245 and accompanying text.

167. *See infra* notes 219-222 and accompanying text.

Terry stop, the precise quantification would not have helped individual officers in making their on-the-spot decisions. It makes more sense for officers to be given some broad guidelines (e.g., "more than a mere hunch" or "some level of objective justification required") and then teach them through training and trial and error what courts will approve and what they will not (e.g., observing a suspect leave a known crack house and then run from a uniformed police officer constitutes reasonable suspicion; observing a suspect leave a known crack house with no other suspicious behavior does not). Similarly, telling a magistrate that she should only issue the warrant if there is a 45% chance of finding contraband would be unlikely to help her make the decision in a world of clinical judgments. The magistrate must consider the myriad of subjective factors from the police officer's affidavit: the credibility of an informant, the reports of unusual but not blatantly illegal activity, and so on. Given the messiness of the evidence confronted by police and judges, a messy standard makes the most sense. Such a standard allows the decision-makers to follow their intuition and make a subjective judgment about whether "something seems not right about this situation" (reasonable suspicion) or "I believe there is a good chance that a crime has been committed" (probable cause).[168] Indeed, many judges who were polled about percentages for probable cause and reasonable suspicion in the 1981 survey refused to answer the questions, arguing that using percentages would be "misleading because burdens of proof deal with qualitative judgments rather than quantitative judgments."[169]

Numerous scholars have also objected to creating specific quantifiable standards. For example, Professor Orin Kerr argues that quantification of probable cause would lead to less accurate probable cause determinations because warrant applications only provide a limited amount of information, and under the current system, judges are able to use their intuition to account for the missing facts.[170] Professor Kerr argues that when a judge gets a warrant application,

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168. Judges seem to reject quantitative standards as well. Rita James Simon, *Judges' Translations of Burdens of Proof into Statements of Probability*, *in* THE TRIAL LAWYER'S GUIDE 113 (John J. Kennelly, James P. Chapman & William J. Harte eds., 1969). In the survey of 400 trial court judges from the late 1960s, judges were asked whether they would approve of using specific percentages or probabilities in determining standards of proof, and "[t]he judges were almost unanimous in their rejection of the proposal for both criminal and civil trials." *Id.*

169. McCauliff, *supra* note 165, at 1332.

170. Kerr, *supra* note 146, at 132.

she only sees the selective facts that the police want her to see: investigative techniques that successfully found evidence to build towards probable cause.[171] But the application will not describe any investigative techniques that were used that failed to find evidence nor will it describe any possible investigative techniques that could have been used that were not used.[172] In the current non-quantified world, Professor Kerr argues, judges can use their intuition about what might be missing from the warrant application, and judges will instinctively (and perhaps subconsciously) factor that into their decision.[173] If the probable cause standard became quantified, at, say, 40%, judges would merely calculate the odds (incorrectly) based on the selective facts in the affidavit and would suppress their natural intuition to be suspicious about the facts that might not have been included.

Although Professor Kerr claims his argument is based on the value of judicial intuition, it is really about the need for particularized suspicion. He uses an example of law enforcement who have a well-documented study that 60% of all Harvard dorm rooms contain illegal drugs, and he posits that police officers attempt to use that study to get a warrant to search a specific dorm room.[174] A judge would rightfully be suspicious of this request, he argues, because the judge's intuition would make her wonder why the police have chosen this room in particular—thus leading to the conclusion that she is not getting the full story from the police.[175] But this is merely a restatement of the requirement that suspicion be particularized—that the affidavit must contain some information that links this specific suspect to the illicit activity. And as noted above,[176] this is an important consideration in designing big data's algorithms for criminal law application—we need to either ensure that the inputs contained some reference to the individual actions or behavior of the suspect himself, or allow for police and judges to add in their own observations of individual activity.[177]

171. *Id.* at 133-34.

172. *Id.*

173. *Id.* at 137-39.

174. *Id.* at 135-37.

175. *Id.* at 138-39.

176. *See supra* Section II.B.

177. Professor Kerr's objection to quantification also focuses on the inability of judges to use specific numerical probabilities in their decision-making process and the cognitive biases that would prevent them from using probability numbers appropriately. For example, Professor Kerr discusses the representative heuristic and anchoring effects, both of which tend to make individuals misjudge numerical

A more troubling critique of using predictive algorithms is the Supreme Court's requirement that the decision-maker use a "totality of the circumstances" test in determining whether reasonable suspicion or probable cause exist.[178] Professor Michael Rich argues that a predictive algorithm can never determine probable cause on its own because the algorithm is by definition limited in the factors that it considers in making its determination.[179] A predictive algorithm might be programmed to consider only a handful of factors, or it might be programmed to consider hundreds of factors, but it can never consider every factor that could possibly be relevant to a probable cause analysis.[180] A human being at least has the potential to incorporate new observations, but a predictive algorithm is limited by its previous programming.[181]

One response to this critique is that it somewhat misrepresents what the Court means by "totality of the circumstances." This requirement does not mean that the decision-maker must consider every possible factor—that would be impossible for a human being or a computer. Indeed, courts have noted that once a police officer has established that probable cause exists, the officer is under no further duty to investigate or gather exculpatory data.[182] Instead, "totality of the circumstances" means two things.

First, courts should reject a formalistic checklist of factors (such as the pre-Gates "two pronged" test)[183] and be willing to consider many different factors in deciding whether probable cause

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probabilities, sometimes quite dramatically. This argument has broader implications for adopting big data's mechanical predictions, which will be discussed in Section III.B, *infra*.

178. *See* Illinois v. Gates, 462 U.S. 213, 230-31 (1983).

179. *See* Rich, *supra* note 148, at 897-98.

180. *Id.* at 897.

181. *Id.* Professor Rich gives an example of a predictive algorithm that considers location, time of day, facial recognition technology, prior criminal activity and other background information, and then adds in the specific behavior that a certain suspect is approaching multiple people on the street and briefly engaging in a hand-to-hand transaction with each of them. *Id.* at 898. The algorithm predicts a strong possibility of drug dealing. *Id.* A police officer who investigates notices that (1) the suspect does not change his behavior when he sees the police officer; and (2) a person who just engaged in a hand-to-hand transaction with the subject drops a church flyer on the ground immediately after the encounter. *Id.* The predictive algorithm did not account for these extra observations, which almost certainly obliterate the probable cause conclusion, but any human being would be able to process this new data appropriately. *Id.*

182. *See* Ahlers v. Schebil, 188 F.3d 365, 371 (6th Cir. 1999).

183. *See, e.g.*, Aguilar v. Texas, 378 U.S. 106, 114 (1964).

exists.[184] Certainly a predictive algorithm can be designed to consider hundreds of different factors, far more than the average police officer observing the scene and far more than are typically included in an affidavit in a warrant application.[185] It is true that no predictive algorithm will ever be able to consider every relevant factor, whether inculpatory or exculpatory. But of course this is also true for police officers and judges. In fact, predictive algorithms could conceivably process thousands of different factors, many more than a human being could.

It is easy to come up with examples of cases in which a police officer makes an observation that is not programmed into the predictive algorithm and which dramatically increases (or decreases) the level of suspicion in a situation, but it is equally easy—if not easier—to think of examples in which a predictive algorithm considers relevant factors that an average police officer would never consider. Many of the factors that human police officers consider to be relevant may in fact be irrelevant or may be given insufficient weight or too much weight. And, as many commentators have pointed out, some of the "intuitions" of police officers and even judges are grounded in implicit racial bias, making their conclusions not just inaccurate but also discriminatory.[186]

Second, the police and courts must also consider potential exculpatory evidence as part of the totality of the circumstances, since certain observations or background facts may lower the level of suspicion.[187] Predictive algorithms can—and should—be programmed to consider possible exculpatory evidence as well, and to weigh that evidence in reaching their conclusions.

In short, quantifying these standards will allow police and judges to use predictive algorithms, bringing a number of benefits: the opportunity to reduce discriminatory bias in the system; greater accountability for police actions; and a higher level of accuracy (that is, fewer searches of those who are innocent and more searches of

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184. Illinois v. Gates, 462 U.S. 213, 230-33, 238-39 (1983). The Supreme Court noted that a magistrate's job in reviewing a warrant application was "simply to make a practical, commonsense decision whether, given all the circumstances set forth in the affidavit before him, including the 'veracity' and 'basis of knowledge' of persons supplying hearsay information, there is a fair probability that contraband or evidence of a crime will be found in a particular place." *Id.* at 238.

185. *See* Rich, *supra* note 148, at 895-901.

186. *See id.* at 897-900; L. Song Richardson, *Police Efficiency and the Fourth Amendment*, 87 IND. L.J. 1143 (2012); *see also supra* notes 121-126 and accompanying text.

187. *See, e.g.*, Gardenhire v. Schubert, 205 F.3d 303, 318 (6th Cir. 2000).

those who are in fact engaged in criminal activity). There is nothing inherent about these tests that would forbid courts from adopting quantitative standards, but courts have been extremely reluctant to do so.[188] In the next Part, we will talk about the feasibility of such a shift.

III. MAKING BIG DATA WORK IN THE CRIMINAL JUSTICE SYSTEM

Under current law, a police officer seeking a search warrant states that she believes there is probable cause to believe that contraband will be found in the suspect's house, and a judge appraises that assertion by reviewing and evaluating the facts that the police officer places in her affidavit, including the credibility of any informants (and of the police officer herself). The judge then reaches her own conclusion about whether a person of reasonable caution would believe that contraband is present at the location.

In a world of predictive algorithms, the police officer will instead present the magistrate with the output of a computer program which states that there is a 40% chance that contraband will be found in the suspect's house. The judge will then examine the algorithm that was used to ensure that it meets the appropriate legal standards and will then make a ruling as to whether the 40% prediction is sufficient to establish probable cause. Depending on the circumstances, the judge may make a decision based solely on the output of the algorithm (the "outcome determinative" model), or she may consider the output of the algorithm as one factor to combine with other relevant facts (the "formal factor" model).

As we have seen in the previous Parts, in order to reach this world we must overcome a number of obstacles. First, the judge needs to know that the computer is not using discriminatory factors or data that merely reinforces past discrimination. Second, the judge will need to confirm that at least some of the factors used by the computer are specific to this particular suspect and that the 40% figure is not merely derived from aggregate group probability figures. If the algorithm has no factors that are based on individualized suspicion, a judge needs to combine the 40% result with specific facts about this particular suspect in order to arrive at her own prediction. And finally, we need to know whether the 40% chance of finding contraband (or whatever number the judge settles on after factoring in other information) is sufficient to convince a

188. *See supra* notes 159-161 and accompanying text.

judge that a person of reasonable caution would believe that contraband is present. In order to overcome this final problem, courts must overcome their hostility to quantifying the legal standards that make up the backbone of criminal procedure.

Thus, in order to create a system where police officers and judges use data-centric mechanical predictions in making their decisions, two major changes must occur. First, the predictive algorithms must be sufficiently transparent to allow judges to ensure that the algorithm is not relying upon unconstitutional factors, either directly or indirectly, in reaching its conclusions. Transparency is also required so that judges can ensure that at least some of the factors leading to this number are specific to this particular suspect. And as we will see, transparency is also necessary so that judges can add additional factors to these algorithms in order to adjust their results to the facts of a specific case. Second, courts must overcome their resistance to quantifying these legal standards, so that the numerical results from mechanical predictions can be applied to these legal determinations. As part of overcoming that reluctance, in some cases judges must also become comfortable with manipulating these probabilities and combining them with other factors in order to reach their own independent conclusions.

A. Transparent Algorithms and Data Sets

The first step is to convince companies who make these algorithms to share the details of their operation—if not the source code, at least the factors that their predictive models consider and the weight that the models assign to each factor. The transparency requirement is necessary not only for the algorithm itself but also for the underlying data sets, in order to avoid the ratchet effect discussed earlier.[189] Courts need to be able to examine the underlying evidence being used by the algorithm to ensure that they are not already tainted by race or by proxies for race—and if they are, the data sets need to be adjusted in order to remove the taint. Greater transparency for the data sets will also help with another growing problem with our increasing reliance on big data: erroneous information in the government and private databases upon which these algorithms rely.[190] As we have seen earlier, police are already relying on these predictive algorithms to direct resources and place certain people

189. *See supra* notes 134-136 and accompanying text.
190. *See* Logan & Ferguson, *supra* note 135, at 13-14.

under suspicion, so cleansing the algorithms of discriminatory factors and purging inaccurate information is already long overdue.

Another reason to mandate transparency is to ensure that the individualized suspicion requirement is met. As noted above,[191] some predictive algorithms may base their conclusions solely on group membership and external factors, thus violating the legal requirement that reasonable suspicion or probable cause be based on individualized suspicion. If the inputs used by the algorithm are open for the judge to examine, then she can ensure that the conclusion is based on the appropriate level of individual activity. And if there are no inputs based on individualized suspicion, the judge must demand additional facts from the law enforcement officer in order to establish individualized suspicion—that is, she will be forced to switch from an "outcome determinative" use of predictive algorithms to a "formal factor" model.

Unfortunately, up until now, companies have been extremely secretive about the details of their predictive algorithms, presumably because they consider these details to be valuable proprietary information.[192] The company that provides the Beware software to police departments does not even allow the police departments to know the details of the algorithm.[193] Recently, the American Civil Liberties Union (ACLU) had to make a public records request to the Fresno police, seeking information about the factors used by its predictive software; the results still did not provide anything like the kind of transparency necessary to evaluate the constitutionality of the program.[194] This secrecy is not limited to private corporations; even

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191. *See supra* notes 145-155 and accompanying text.

192. Jouvenal, *supra* note 30.

193. George Hostetter, *In Wake of Paris, Fresno P.D. Rolls out Big Data to Fight Crime*, CVObserver (Nov. 16, 2015), http://www.cvobserver.com/crime/in-wake-of-paris-fresno-p-d-rolls-out-big-data-to-fight-crime/4/ [https://perma.cc/7MNX-ZB8B]. For example, the police were asked at a city council meeting whether a misdemeanor conviction alone would be enough for the program to conclude that the suspect was "red," the highest level of danger. *Id.*

194. Matt Cagle, *This Surveillance Software Is Probably Spying on #BlackLivesMatter*, ACLU S. Cal. (Dec. 15, 2015), https://www.aclusocal.org/mediasonar/ [https://perma.cc/58YX-LATJ]. The result of the public records request was eighty-eight pages of emails that included lists of "high frequency social media terms" that could be indicative of criminal activity. *Id.* (follow "88 pages of documents" hyperlink; then see E-mail from Media Sonar to Angeline MacIvor (Jan. 27, 2015, 10:43 AM), http://www.aclunc.org/docs/201512-social_media_monitoring_softare_pra_response.pdf [https://perma.cc/93NK-YC3V]).

private individuals who design these algorithms refuse to disclose exactly how they work.[195]

Thus far, this secrecy has not posed significant legal problems, since predictive algorithms are only being used to direct police resources. But this is likely to change in the near future, regardless of whether police and courts begin to use predictive algorithms to establish legal cause to stop or search. There is growing concern that the use of mechanical predictions is merely a sophisticated form of racial profiling,[196] and if police want to continue to use algorithms in any capacity, they will need to reveal (or require their client companies to reveal) the details of these algorithms. This greater transparency will not only reassure the public (and the courts) that the determinative factors used by the algorithm are not related to race, but it will also lay the groundwork for adopting these algorithms more formally into the legal system. And, not incidentally, it may reveal that some algorithms are relying on forbidden factors in reaching their conclusions, which of course would require the algorithm to be redesigned with the offending factors removed. The ACLU's recent public records request, for example, revealed that one of the Fresno Police Department's predictive software algorithms used the social media hashtag #BlackLivesMatter as a risk factor for "police hate crimes."[197]

But requiring the software engineers and statisticians who design mechanical predictions to reveal the factors being used and the weights assigned to each factor is only the first step. Modern day predictive software is not static; the more sophisticated algorithms will adjust the factors as they go, learning from past experience. As

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195. Stroud, *supra* note 33. In fact, the Chicago Police Department refused to even reveal the names of the people on their "heat list," because they argue such disclosure could endanger the safety of law enforcement officers or the general population. *Id.* They have revealed some of the factors that they use, such as criminal records, social circles, gang connections, and whether the suspect has been a victim of an assault or a shooting. *See* Eligon & Williams, *supra* note 36. Unfortunately, a partial release of certain factors does little to address the transparency concerns discussed in this Article.

196. *See* Alexis C. Madrigal, *The Future of Crime-Fighting or the Future of Racial Profiling?: Inside the Effects of Predictive Policing*, HUFFINGTON POST (Mar. 28, 2016, 7:54 AM), http://www.huffingtonpost.com/entry/predictive-policing-video_us_56f898c9e4b0a372181a42ef [https://perma.cc/BK5D-V9JM].

197. Cagle, *supra* note 194 (follow "88 pages of documents" hyperlink; then see E-mail from Media Sonar to Angeline MacIvor (Jan. 27, 2015, 10:43 AM), http://www.aclunc.org/docs/201512-social_media_monitoring_softare_pra_response.pdf [https://perma.cc/93NK-YC3V]).

the algorithm makes thousands or millions of predictions, it will be told which of those predictions ended up being accurate, and it will change the weight assigned to each of its factors accordingly to improve its accuracy. This process, known as machine learning,[198] ensures that the algorithm's mechanical predictions improve with time, but it makes it even more difficult for the courts to evaluate the degree to which each factor is relevant to the machine's conclusions.[199] As one scholar has noted, "[F]orecasting becomes a distinct activity that differs from explanation. . . . What matters most is forecasting accuracy. Combining explanation with forecasting can compromise both."[200] In other words, the most accurate algorithms—those that use machine learning to sift through millions of different data points—may be the least transparent.[201]

However, as we have seen in other contexts in the criminal justice system, it is possible to overcome these obstacles. A judge does not really need an intricate understanding of the underlying code of the algorithm; she only needs to know (1) the factors that the algorithm used and (2) the historical accuracy of algorithm's results.[202] Although the experts who design the algorithm need to consider hundreds or thousands of data points in order to determine which ones are the most predictive, for practical reasons the actual algorithm will probably only use eight or nine factors, just like the sentencing risk assessment tools.[203] Thus, the first piece of

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198. Machine learning is defined as the following process: "A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P*, if its performance at tasks in *T*, as measured by *P*, improves with experience *E*." TOM M. MITCHELL, MACHINE LEARNING 2 (1997).

199. *See* RICHARD BERK, CRIMINAL JUSTICE FORECASTS OF RISK: A MACHINE LEARNING APPROACH 110-11 (2012).

200. *Id.* at 111.

201. *See* Rich, *supra* note 148, at 886 ("Absent an intentional decision to the contrary, machine learning tends to create models that are so complex that they become 'black boxes,' where even the original programmers of the algorithm have little idea exactly how or why the generated model creates accurate predictions. On the other hand, when an algorithm is interpretable, an outside observer can understand what factors the algorithm relies on to make its predictions and how much weight it gives to each factor. Interpretability comes at a cost, however, as an interpretable model is necessarily simpler—and thus often less accurate—than a black box model.").

202. Some would argue that the judge would also need to know the weights that the algorithm assigned to each factor, so that the judge would be better able to accurately add in other factors if she was using a "formal factor" model. If so, the program could be designed to provide explicit percentages for each factor every time it produces a result.

203. *See supra* notes 72-76 and accompanying text.

information should be easy for law enforcement to provide, since presumably it is law enforcement officers who input the data. And the accuracy of the results should easily be available, since an integral part of developing big data's algorithms is to calculate (and then improve on) the accuracy of the predictions that are being made.

Once the judge obtains this information, she would then need to evaluate (1) whether the specific inputs are proxies for a forbidden factor, such as race,[204] and (2) whether they contain sufficient particularity to justify the stop, search, or arrest.[205] In other words, the judge does not need to know exactly how the algorithm arrived at its results, only which factors it considered in doing so. The judge would also have to determine whether the accuracy of the algorithm is sufficient to meet the reasonable suspicion or probable cause standard, a question we turn to in the next Section.

And if a judge did want to understand the way the algorithm processed the inputs, she would not have to personally decipher the meaning of the underlying source code, much less understand the evolution of the data in a machine learning environment. Just as judges hear from experts in a *Daubert* hearing when they are called upon to determine the reliability of a new and complex scientific process, a judge who is called upon to evaluate the methodology and reliability of a predictive algorithm could also listen to experts testifying from both sides.[206]

This transparency requirement should be seen not as a weakness of adopting mechanical predictions but as one of its strengths. Courts currently rely on a combination of their own intuition (an internal, subjective algorithm) and experience (an internal, limited database) when reviewing the decisions of a police officer (decisions that are made based on a combination of the police officer's intuition and experience). It has already been conclusively demonstrated that these intuitions are subject to significant levels of racial bias,[207] but it is difficult for a magistrate to know if (or to what degree) her own intuition may be suffering from this problem. Likewise, the magistrate's personal experiences are likely based in part on problematic data. These hidden biases are very difficult to

204. *See supra* Subsection II.A.1.
205. *See supra* Section II.B.
206. Daubert v. Merrell Dow Pharm., 509 U.S. 579, 597 (1993).
207. *See supra* notes 119-120 and accompanying text.

remove from a person's decision-making process.[208] With the proper transparency requirements, however, these biases can be easily detected in algorithms and data sets of mechanical predictions.

B. Quantifying the Legal Standards

Lack of transparency is not only a problem for those who collect and process the data, but also for those who use the data—that is, the judges who apply the legal standards. If the quantified results from the world of big data are going to be used effectively in the courts, judges will need to update the legal standards that they use.

1. *Setting a Number*

Perhaps the most challenging aspect of adopting predictive algorithms is determining the quantified percentage to match up with reasonable suspicion or probable cause.[209] The vagueness of the current rules obscures any attempt to determine how much suspicion is actually necessary to reach these standards, and courts have routinely stated that these standards should not or even cannot be reduced to mere numerical probabilities.[210] But if the criminal justice system is going to benefit from the increased accuracy and potential reduction of unfair bias that is offered by predictive algorithms, courts will need to overcome their hostility to quantification.

Quantifying these standards may lead to other benefits as well. One positive side effect of greater quantification is the possibility of creating precise standards for different situations—what Professor Christopher Slobogin refers to as the proportionality principle.[211] Courts (or legislatures) could craft specific standards for the most intrusive searches (such as wiretaps or bodily intrusions) and lower

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208. *See* Sendhil Mullainathan, *Racial Bias, Even When We Have Good Intentions*, N.Y. TIMES (Jan. 3, 2015), http://www.nytimes.com/2015/01/04/upshot/the-measuring-sticks-of-racial-bias-.html?abt=0002&abg=1 [https://perma.cc/6QBT-6BJA].

209. As the use of predictive algorithms becomes more widespread, other legal standards, such as "flight risk" in the bail context, may also need to be quantified. *See supra* Section I.D.

210. *See supra* notes 159-164 and accompanying text.

211. Christopher Slobogin, *Let's Not Bury* Terry*: A Call for Rejuvenation of the Proportionality Principle*, 72 ST. JOHN'S L. REV. 1053, 1081-85 (1998) [hereinafter Slobogin, *Proportionality Principle*]; *see also* CHRISTOPHER SLOBOGIN, PRIVACY AT RISK: THE NEW GOVERNMENT SURVEILLANCE AND THE FOURTH AMENDMENT 31-41 (2007).

standards on a sliding scale as searches become less invasive (searches of homes, searches of cars, searches of offices, frisks, flyovers, surveilling public spaces).[212] Of course, courts and legislatures already have created these different standards to some degree,[213] but the lack of quantification has made this process confusing and limited the number of "tiers" that can realistically be created.

Other commentators have argued that quantifying the probable cause standard would enable courts to adopt a sliding scale based on the severity of the crime being investigated.[214] Courts have so far been reluctant to entertain this idea, generally holding that one standard should apply across the board to every criminal investigation.[215] But as Professor Craig Lerner has pointed out, courts have dropped some hints that the probable cause standard should be lower for police investigating a mass shooting or a kidnapped child than they would be for a low-level drug possession case.[216] Judge Richard Posner, for example, writing an en banc decision for the Seventh Circuit, held that probable cause should be "a function of the gravity of the crime" in the context of exigent circumstances.[217]

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212. Slobogin, *Proportionality Principle*, *supra* note 211. Professor Slobogin would also require a greater showing for the most intrusive searches, such as wiretaps or bodily intrusions; not just a 75% likelihood but also "clear and convincing proof that the evidence thereby sought is crucial to the state's case and that the search will be conducted in the least intrusive manner possible." *Id.* at 1082-83.

213. *See* Ric Simmons, *The New Reality of Search Analysis: Four Trends Created by New Surveillance Technologies*, 81 MISS. L.J. 991, 999-1004 (2012).

214. *See, e.g.*, Craig S. Lerner, *The Reasonableness of Probable Cause*, 81 TEX. L. REV. 951, 1014-22 (2003); Joseph D. Grano, *Probable Cause and Common Sense: A Reply to the Critics of* Illinois v. Gates, 17 U. MICH. J.L. REFORM 465, 504-05 (1984); Albert W. Alschuler, *Bright Line Fever and the Fourth Amendment*, 45 U. PITT. L. REV. 227, 229-31 (1984).

215. *See, e.g.*, Dunaway v. New York, 442 U.S. 200, 208 (1979).

216. Lerner, *supra* note 214, at 1015-17. Professor Lerner ultimately proposes a formula for determining probable cause, similar to the Learned Hand formula for negligence claims, which takes into account the severity of the crime and the intrusiveness of the search. *Id.* at 1019-22.

217. Llaguno v. Mingey, 763 F.2d 1560, 1566 (7th Cir. 1985) (en banc). Other Justices and judges have also hinted at the need for a sliding scale, though the hints are usually made in dissents. *See, e.g.*, Brinegar v. United States, 338 U.S. 160, 183 (1949) (Jackson, J., dissenting) (arguing that the societal interest in searching a car trunk for a kidnapped child was greater than the societal interest in searching a car trunk for bootlegged alcohol, and thus he would be tempted to make an "exception" to the Fourth Amendment in the former case); United States v. Soyka, 394 F.2d 443, 452 (2d Cir. 1968) (en banc) (Friendly, J., dissenting) ("[T]he gravity

This type of sliding scale would be all but impossible to administer with the current broad standards; only with greater precision can courts make meaningful distinctions in different contexts.

Professor Erica Goldberg also points out that the imprecise nature of the current standards for probable cause tends to create a very low bar in practice because of the good faith exception to the exclusionary rule.[218] Under this exception, even if a reviewing court finds that a warrant lacked probable cause, the illegally obtained evidence will still be admissible as long as the officer acted in good faith—that is, as long as the warrant was not "so lacking in . . . probable cause as to render official belief in its existence entirely unreasonable."[219] A vague probable cause standard means that many warrants that fall short of the probable cause standard will in practice result in evidence that can be used in trial, as long as the lack of probable cause was not obvious to the officer.[220] If the probable cause standard were quantified, it could also be enforced with more regularity against police officers, who would be much less able to claim the good faith exception when a warrant did not in fact meet the proper standard.

There is a possibility that if we use actual data to run these analyses, we will learn that our standards for stops, arrests, and warrants are embarrassingly low. For example, we may learn that the standard hit rate for *Terry* stops is 2% and the average hit rate for search warrants is 10%—that is, that police officers conduct *Terry* stops on individuals with only a one in fifty chance that the suspect is engaged in criminal activity; and judges are issuing search warrants even though there is only a one in ten chance of finding contraband at the named location. We may also learn that these rates vary wildly depending on the jurisdiction,[221] the suspected crime, and (as we have already seen) the race of the suspect.[222] This information will be yet another fringe benefit of shifting to a quantitative model. If courts learn that they are in fact using a 2% rate for reasonable suspicion, we can have a real debate about whether this number is too low, and if so, what the number ought to be. Such a debate is

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of the suspected crime and the utility of the police action [should be] factors bearing on the validity of the search or arrest decision.").

218. *See* Goldberg, *supra* note 148, at 802-05.

219. United States v. Leon, 468 U.S. 897, 923 (1984).

220. *See* Goldberg, *supra* note 148, at 804-05.

221. *See id.* at 802-03.

222. *See supra* note 120 and accompanying text.

nearly impossible to have now because the current standards are shrouded in intentionally ambiguous legalese.

Once we agree on a number, that number can be imposed consistently throughout the country. No longer will individuals in the city be subjected to one standard while individuals in the suburb receive a more deferential standard. Similar standards will apply to those suspected of tax fraud as to those suspected of possessing heroin. This type of equality is simply not feasible under our current system.

Yet another benefit to quantification will be greater transparency in the factors that police and courts use to make these decisions.[223] For example, consider the case law surrounding *Terry* frisks, which shows courts struggling to determine when there is reasonable suspicion to believe a suspect is armed. One commonly cited factor is the type of crime the person is suspected of having committed. Courts have consistently held that some crimes, such as robbery,[224] narcotics trafficking,[225] growing large amounts of marijuana,[226] rape,[227] or burglary,[228] all involve a high risk of the suspect carrying a weapon and are thus a legitimate factor in determining whether the suspect is armed.[229] But is the nature of the crime enough on its own to create reasonable suspicion? Is it enough when combined with one other observation by the police officer, such as a "furtive move" or a "suspicious bulge"?

Generally, courts will find that if the officer reasonably believes that the suspect is guilty of one of these "weapons likely"

223. *See, e.g.*, Barry Jeffrey Stern, *Warrants Without Probable Cause*, 59 BROOK. L. REV. 1385, 1436-37 n.172 (1994) (noting that the Supreme Court "has not defined [the probable cause] standard in a manner that is particularly illuminating to those charged with enforcing and interpreting the criminal law"); Goldberg, *supra* note 148, at 833 (noting that even in the absence of quantitative evidence, "assigning a numerical value to probable cause can still assist judges in making probable cause determinations, so long as they appreciate that this number serves only as a reference").

224. *See, e.g.*, Terry v. Ohio, 392 U.S. 1, 28 (1968).

225. *See, e.g.*, United States v. $109,179 in U.S. Currency, 228 F.3d 1080, 1086-87 (9th Cir. 2000).

226. *See, e.g.*, United States v. Davis, 530 F.3d 1069, 1082-84 (9th Cir. 2008).

227. *See, e.g.*, People v. Shackelford, 546 P.2d 964, 966-67 (Colo. App. 1976).

228. *See, e.g.*, United States v. Mattarolo, 209 F.3d 1153, 1158 (9th Cir. 2000).

229. As it turns out, the court's assumptions about which crimes carry a high chance of weapons being present is sometimes correct and sometimes not. The Bureau of Justice study revealed that a person committing a robbery does have a high probability of carrying a weapon (34.5%), but that burglary (4%), sexual assault (2.9%) and narcotics trafficking (7.8%) do not. HARLOW, *supra* note 52, at 3.

crimes, then that belief is sufficient to create reasonable suspicion that a suspect is armed.[230] But surely the risk of a suspect carrying a weapon is not identical for all five of those crimes—so in theory courts should require some corroboration in the case of certain suspected crimes and less (or none) in the case of others. This is not what happens: Courts merely state that the suspected crime is "likely to involve the use of weapons"[231] and then generally find that the frisk was justified. Meanwhile, other suspected crimes, such as passing counterfeit money[232] or possession of illegal drugs,[233] are held to not be a legitimate factor—that is, an individual suspected of these crimes has absolutely no greater likelihood than anyone else to be carrying a weapon. In reaching these conclusions, courts generally rely on their intuition rather than any actual evidence that indicates the prevalence (or dearth) of weapons on suspects who commit these crimes. And in the absence of empirical evidence, courts create a false binary categorization: Suspicion of certain crimes generates reasonable suspicion on its own, while suspicion of other crimes does not add to the probability of a weapon being present.

Occasionally, courts do venture into the realm of data when deciding whether reasonable suspicion or probable cause exist, with decidedly mixed results. In a recent case, the Ninth Circuit attempted to determine if suspicion of domestic violence was a legitimate factor in determining whether the individual was armed.[234] The majority held that suspicion of domestic violence did not increase the likelihood of the suspect possessing a weapon. To support its conclusion, the court cited studies that concluded that "domestic violence calls for service account for a relatively small proportion of the overall rate of police officers murders" and that 36.7% of domestic violence victims had at some point in their lives been threatened or harmed by a weapon during a domestic violence incident.[235] The dissent cited FBI studies demonstrating that 33% of assaults on police officers in a recent year were committed while police were responding to "disturbance calls," which is "a category which includes domestic violence calls," and that over a ten year period three times more police officers were killed responding to

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230. *Terry*, 392 U.S. at 28.
231. *Id.*
232. *See, e.g.*, United States v. Thomas, 863 F.2d 622, 629 (9th Cir. 1988).
233. *See, e.g.*, Ramirez v. City of Buena Park, 560 F.3d 1012, 1022 (9th Cir. 2009).
234. Thomas v. Dillard, 818 F.3d 864, 878 (9th Cir. 2016).
235. *Id.* at 880-81.

domestic violence calls than those responding to burglary calls.[236] None of these studies establish any quantitative probability that perpetrators of domestic violence use or carry weapons; they merely establish the undeniable fact that perpetrators of domestic violence sometimes carry weapons and sometimes pose a risk to police officers.[237]

The court did cite one seemingly useful study: a Bureau of Justice report covering seven years, which concluded that 15% of domestic violence attacks involved a weapon.[238] But this statistic is almost certainly too crude to be useful. Like "burglary" or "narcotics trafficking," the crime of domestic violence encompasses many different kinds of behavior—some of them probably linked to a high likelihood of weapons possession and some linked to a relatively low likelihood.[239] In order to effectively use statistics, courts will need more sophisticated and detailed data, which can be applied to the facts of the specific case—did the alleged domestic violence occur at home or in a public place? What percentage of individuals living in the neighborhood possess firearms? Are the police responding at night or during the daytime? This type of detailed data needs to be developed so that it can be used by the courts—without it, courts may identify these factors as relevant but then apply their own flawed intuition as to how each factor affects the ultimate question of reasonable suspicion.

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236. *Id.* at 898 (Bea, J., concurring in part and dissenting in part).

237. The regular inability of courts to effectively and accurately use statistics has led some commentators to argue against quantifying legal standards such as probable cause because judges are not generally skilled at mathematics and statistical analysis. *See, e.g.*, Max Minzner, *Putting Probability Back into Probable Cause*, 87 TEX. L. REV. 913, 951 (2009); Kerr, *supra* note 146, at 132. However, as noted below, courts already use statistical evidence to some extent in evaluating reliability of different tools used by law enforcement officers. *See infra* notes 238 and accompanying text. Courts also use statistical evidence in evaluating and applying expert testimony. *See* Daubert v. Merrell Dow Pharm., 509 U.S. 579, 597 (1993). Furthermore, since judges are "repeat players" in reviewing reasonable suspicion and probable cause determinations, they will develop an expertise with statistics in the probable cause context as the results of predictive algorithms become more widespread. *See* Minzner, *supra* note 237, at 954-55.

238. *Dillard*, 818 F.3d at 896-97 (Bea, J., concurring in part and dissenting in part) (citing CALLIE MARIE RENNISON, BUREAU OF JUSTICE STATISTICS, INTIMATE PARTNER VIOLENCE AND AGE OF VICTIM, 1993-99 7 (Oct. 2001), http://www.bjs.gov/content/pub/pdf/ipva99.pdf [https://perma.cc/UH2V-UQ4G]).

239. The Ninth Circuit acknowledged this in its opinion, noting that "domestic violence calls vary widely in the actual threats they pose to officers and others." *Dillard*, 818 F.3d at 881 (majority opinion).

Of course, even if better data were available, the data would be insufficient without a quantitative standard to judge it against. Assume that the court had access to a database that stated that of all the domestic violence calls in this neighborhood during this time of day in the past five years, 19.2% of the suspects were armed when the police arrived. Would that constitute reasonable suspicion? If not, how close is it—close enough that a suspicious movement by the suspect is enough to put the risk across the line?[240] Without a quantified definition of reasonable suspicion, judges are unable to answer these questions, and so instead they create an inaccurate binary distinction among different types of crimes.

Thus, we need to set a quantified percentage chance for reasonable suspicion or probable cause. As we saw earlier, judges appear to have widely divergent views as to this question, with survey results varying widely but averaging at 30.8% for reasonable suspicion and 44.5% for probable cause.[241] The Supreme Court has implied[242]—and lower courts have stated[243]—that the probable cause standard does not mean "more probable than not," which places the probable cause standard at less than 50%. Most commentators also agree that probable cause is something close to but just less than 50%,[244] while scattered evidence from prosecutors and law enforcement point to numbers between 40% and 51%.[245]

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240. Here is an example of where Bayesian analysis would be useful—courts would start with a 15% baseline and then add in other factors to increase or decrease the likelihood. *See infra* notes 276-277 and accompanying text.

241. *See supra* notes 165-166 and accompanying text. The median numbers were 30% for reasonable suspicion and 50% for probable cause.

242. Illinois v. Gates, 462 U.S. 213, 235 (1983) (stating that the "[f]inely tuned standards such as proof beyond a reasonable doubt or by a preponderance of the evidence . . . have no place" in determining whether probable cause exists). The Supreme Court also stated that probable cause represents only "a fair probability" that contraband or evidence of a crime will be found, which implies something less than 50%. *Id.* at 246. A plurality of the Supreme Court has stated that probable cause does not require that the fact being asserted be "more likely true than false." Texas v. Brown, 460 U.S. 730, 742 (1983).

243. *See, e.g.*, United States v. Garcia, 179 F.3d 265, 269 (5th Cir. 1999); United States v. Travisano, 724 F.2d 341, 346 (2d Cir. 1983).

244. *See* Goldberg, *supra* note 148, at 801 n.62 (listing numerous commentators, most of whom agree that the probable cause standard is less than more-probable-than-not); Ronald J. Bacigal, *Making the Right Gamble: The Odds on Probable Cause*, 74 MISS. L.J. 279, 338-39 (2004) (setting probable cause at a range of 40-49% but warning against too much precision); Daniel A. Crane, *Rethinking Merger Efficiencies*, 110 MICH. L. REV. 347, 356 (2011) (noting that practitioners and commentators estimate probable cause to be "in the 40-45 percent range"). *But see* Slobogin, *Proportionality Principle*, *supra* note 211, at 1082-83

One way to derive a specific number for these standards is to reverse engineer the stops and searches that have been approved under the current law. In other words, we can measure the hit rates for stops and searches that courts have approved using the traditional standards. This should provide us with a number that is at least above the minimum level of suspicion that is required. For example, if across the country, courts approve of 100,000 probable cause searches and police find contraband in 45,000 of those searches, we can know that generally a prediction which is 45% accurate is at least high enough to satisfy the probable cause standard.

Unfortunately, there are not many statistics available, but we do have some actual data from the real world that can be used as a starting point. For example, the district court in the *Floyd* case held that the *Terry* stops in New York City in the early 2000s were often conducted without reasonable suspicion. These stops had a 12% hit rate; thus, the *Floyd* judge apparently considers a 12% rate to be too low.[246] In contrast, we know that before the New York Police Department began its aggressive stop-and-frisk policy, its hit rate for *Terry* stops was a more respectable 21%.[247]

Reviewing probable cause searches of automobiles provides some real-world data as to the percentage chance necessary to establish probable cause. An independent review of the San Antonio police showed that their probable cause automobile searches resulted in a hit rate of 35.1%.[248] As part of a settlement of a federal civil

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(placing the current probable cause level at 50% and the reasonable suspicion level at 30%). Many commentators agree with the courts and say that probable cause should not be quantified. *See, e.g.*, Bruce A. Antkowiak, *Saving Probable Cause*, 40 SUFFOLK U. L. REV. 569, 586 (2007) (arguing that "we should fear any attempt to co-opt mathematical concepts to solve the probable cause riddle"); Grano, *supra* note 214, at 469 (arguing for a "commonsense approach," not a mathematical approach, to probable cause).

245. *See, e.g.*, Lawrence Rosenthal, *The Crime Drop and the Fourth Amendment: Toward an Empirical Jurisprudence of Search and Seizure*, 29 N.Y.U. REV. L. & SOC. CHANGE 641, 680 (2005) (quoting a senior Assistant United States Attorney who estimated the number at 40%); Daniel Richman, *Prosecutors and Their Agents, Agents and Their Prosecutors*, 103 COLUM. L. REV. 749, 783 (2003) (quoting an FBI attorney who set the number at 51%).

246. Floyd v. City of New York, 959 F. Supp. 2d 540, 558-59 (S.D.N.Y. 2013).

247. Jeffrey Goldberg, *The Color of Suspicion*, N.Y. TIMES (June 20, 1999), http://www.nytimes.com/1999/06/20/magazine/the-color-of-suspicion.html?pagewanted=all [https://perma.cc/L75B-A7AR].

248. *See* JOHN C. LAMBERTH, RACIAL PROFILING DATA ANALYSIS STUDY: FINAL REPORT FOR THE SAN ANTONIO POLICE DEPARTMENT 48 tbl.8 (Dec. 2003),

rights action in 1995, Maryland State Troopers were required to report every stop and search of a car on their highways,[249] which showed a 52.5% hit rate for probable cause searches.[250] And a review of the Florida State Police showed a 38.2% success rate for such searches.[251]

Another way to estimate the number is to look at cases involving alerts by drug-sniffing dogs, which can constitute probable cause as long as the dog's reliability has been established.[252] Thus, when a court needs to determine whether a positive alert by a drug dog is sufficient to establish probable cause, the Supreme Court has instructed the reviewing judge to consider the training and past performance of the drug dog in controlled testing environments.[253] Lower courts have already (albeit grudgingly) approved specific numerical success rates for drug dogs as sufficient to establish that the dog's positive alert creates probable cause, holding that accuracy rates of 50%,[254] 55%,[255] 58%,[256] and 60%[257] were all sufficient to satisfy the probable cause standard.[258]

On the other hand, Professor Max Minzner points out that the success rate for search warrants, which allegedly use the same probable cause standard, are much higher—somewhere between

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http://www.mass.gov/eopss/docs/eops/faip/san-antonio-report.pdf [https://perma.cc/WDV7-HS2G].

249. *See* Gross & Barnes, *supra* note 56, at 658.

250. *Id.* at 674 tbl.9.

251. *See* Minzner, *supra* note 237, at 925.

252. Florida v. Harris, 133 S. Ct. 1050, 1057 (2013). Of course, the Harris Court repeated the admonition that the probable cause inquiry in the drug dog context should be a totality of the circumstances test, including not just the drug dog's reliability but also whether the handler gave inappropriate cues or whether the dog was working under unfamiliar conditions. *Id.* at 1057-58. Below we discuss the method for courts to combine the specific quantified numbers from tools (such as drug dogs or predictive algorithms) with other factors. *See infra* Section III.B.2.

253. *Harris*, 133 S. Ct. at 1057-58.

254. United States v. Donnelly, 475 F.3d 946, 955 (8th Cir. 2007).

255. United States v. Anderson, 367 F. App'x 30, 33 (11th Cir. 2010).

256. United States v. Ludwig, 641 F.3d 1243, 1252 (10th Cir. 2011).

257. United States v. Koon Chung Wu, 217 F. App'x 240, 246 (4th Cir. 2007).

258. *See also* United States v. Sanchez-Tamayo, No. 1:10-CR-0532-JOF-JFK, 2011 WL 7767740, at *14 (N.D. Ga. Nov. 28, 2011) (noting that courts have approved a drug dog reliability rate of "approximately 50%-60%" as sufficient to establish probable cause). *But see* United States v. Huerta, 247 F. Supp. 2d 902, 910 (S.D. Ohio 2002) (rejecting probable cause finding even though the drug dog had a 65% success rate).

84% and 97%.[259] Although this dramatic disparity between different applications of the probable cause standard makes it more challenging to determine the "proper" number through reverse engineering, it provides yet another compelling reason to quantify the standard. Are courts being too lenient in reviewing probable cause for warrantless searches, or are they requiring too high a showing for warrant applications? Or perhaps we want two different standards, one for the on-the-spot decisions made by police officers, and one for the greater legitimacy and presumed legality of search warrants? None of these questions can be truly addressed until the probable cause standard is quantified.

From this brief review of the available data, we can see that hit rates for stops and searches vary depending on the jurisdiction and even on the context in which the standard is applied. Thus, if we want to reverse engineer percentages for reasonable suspicion and probable cause from the existing standards, we will need data from a much broader set of studies. However, even the small amount of data that we have so far confirms the estimates of commentators and courts that the number for probable cause is somewhere between 40% and 50%.[260] There is very little data on the success rate for stop and frisks that have been approved by courts, but the *Floyd* case implies that 12% is too low,[261] and we know that the number has to be significantly less than the 40% to 50% range for probable cause.

In one sense, the use of predictive algorithms to establish reasonable suspicion or probable cause is not so revolutionary. The Supreme Court has not been averse to using statistical data in other Fourth Amendment contexts. For example, when the Court was determining whether a drunk driving checkpoint was "reasonable" under the special needs doctrine, it noted that the checkpoint resulted

259. Minzner, *supra* note 237, at 922-23. These rates may be inflated somewhat because some of the jurisdictions that were studied involved police officers who did not return their warrants after the search, presumably because nothing was received. *Id.* at 923 n.38. Even taking into account this possibility, warrant success rates still ranged between 46% and 93%. *Id.* This higher number does not necessarily mean that courts are setting a higher bar for probable cause in warrant applications; it could be that probable cause is always set at, say, 40% for any kind of search, and that most warrant applications achieve a much higher level of success because law enforcement officers want to ensure they get approved when they take the time and expend the resources to apply for a warrant. *Id.* at 922.

260. *See supra* Subsection III.B.1.

261. Floyd v. City of New York, 959 F. Supp. 2d 540, 582-83 (S.D.N.Y. 2013).

in a 1.6% hit rate for drunk drivers[262] and also that similar checkpoints around the country had a 1% hit rate.[263] And as noted above, lower courts already routinely evaluate the reliability of certain tools, such as drug dogs, that are used to demonstrate probable cause.[264] The need for courts to use success rates to evaluate probable cause will only increase as sophisticated investigative technologies such as facial recognition software or gun detectors become more widely used. In a sense, predictive algorithms will be doctrinally no different from these other tools that are already being used to establish probable cause.

2. *Using the Number*

Once a number is set for reasonable suspicion and probable cause, the next step is to decide whether the results from the predictive algorithms will be determinative of the outcome or whether they will merely be one of a number of factors used by officers and judges. As an example, take Professor Andrew Ferguson's modern-day recreation of Detective McFadden observing John Terry on the streets of Cleveland:

> [McFadden] observes John Terry and, using facial recognition technology, identifies him and begins to investigate using big data. Detective McFadden learns through a database search that Terry has a prior criminal record, including a couple of convictions and a number of arrests. McFadden learns, through pattern-matching links, that Terry is an associate (a "hanger on") of a notorious, violent local gangster—Billy Cox—who had been charged with several murders. McFadden also learns that Terry has a substance abuse problem and is addicted to drugs.[265]

Now let us take the next step and assume that the detective plugs all of John Terry's background information into a predictive algorithm, which tells him that John Terry has a 1% chance of being involved in criminal activity at any given time during the day. This result would certainly not be sufficient to create reasonable suspicion. Then our modern Detective McFadden could do some more quick research through the police database and add in some other factors; for example, that Terry has multiple prior convictions for armed robbery of commercial establishments, and license plate

262. Mich. Dep't of State Police v. Sitz, 496 U.S. 444, 454-55 (1990).

263. *Id.* at 455.

264. *See supra* note 252 and accompanying text (referencing Florida v. Harris, 133 S. Ct. 1050, 1057-58 (2013)); Goldberg, *supra* note 148, at 828.

265. Ferguson, *supra* note 12, at 377.

data connects Terry to prior commercial robberies in this area.[266] This, combined with the earlier information about Terry, tells the detective that Terry has a 5% chance of being armed with an illegal weapon at any given time. We still do not have anything like reasonable suspicion. Indeed, it is unlikely that mere background information on a suspect could ever rise to the level of reasonable suspicion—this is akin to saying there are certain people who are so suspicious that there is always reasonable grounds to believe they are engaging in criminal activity anytime they are seen in public.[267]

Regardless of how high the prediction is based on the background information alone, Detective McFadden cannot legally have reasonable suspicion at this point because he has not yet considered any individualized conduct on the part of Terry. So Detective McFadden must incorporate Terry's individualized conduct into the calculus. As it turns out, the detective sees Terry pacing back and forth outside a commercial establishment multiple times, looking in the window, and then conferring with another individual.[268] However, the modern-day Detective McFadden has two options. He can take the 5% chance that Terry is carrying an illegal weapon and then incorporate that into his own subjective calculation, combining that factor with his own observations of Terry pacing, looking, and conferring.[269] Or he can simply input these observations into the algorithm, which would then automatically combine these observations along with other data in order to give a percentage chance that the suspect was in fact involved in criminal activity. The first is an example of using the predictive algorithm as a factor; the second is an example of the "outcome determinative" model.

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266. *Id.* at 378.

267. *See id.* Of course, once predictive algorithms become more sophisticated, we will have a better idea about how high this percentage could be based on only background information. However, because of the particularized suspicion requirement, even if background information alone took us to the required threshold, reasonable suspicion would still not exist.

268. The actual Detective McFadden used these observations alone to arrive at reasonable suspicion. Terry v. Ohio, 392 U.S. 1, 6 (1968).

269. This is the method suggested by Professor Ferguson, who notes that a modern-day Detective McFadden can add the personal observations to the information he gathered from the various police databases to make his finding of reasonable suspicion "easier and, likely, more reliable." Ferguson, *supra* note 12, at 377-78. As explained below, *infra* notes 277-280 and accompanying text, this will require Detective McFadden to engage in a Bayesian analysis, using 5% as a prior probability and then adding in his observations to adjust that probability upwards.

From this basic example, we can see that the "outcome determinative" option has a number of advantages. First, it will be simpler for officers and judges to apply, since it will not require individual officers and judges to process numerical probabilities; the algorithm will literally do all the processing itself and give the decision-maker an exact number. The predictive algorithm will (presumably) use statistics from thousands of previous cases in order to establish whether the relevant facts create the level of suspicion necessary to reach reasonable suspicion or probable cause. These results (and thus the algorithm itself) can be periodically tested every few months to ensure they are still reliable—and as part of that testing, the algorithm can be adjusted to give different weights to different types of data or even to add or remove certain types of data altogether. Second, the outcome determinative model will minimize the potentially biased factors that human decision-makers apply in making these determinations. Both reasonable suspicion and probable cause require the officer to show specific, objective facts to support their conclusion,[270] and forcing police officers to input these specific facts into the algorithm will make it harder for them to consciously or subconsciously use factors based on race.

The purely determinative model could even work in cases where the police officers and judges need to evaluate an informant's reliability to make a probable cause determination. For example, assume that a reliable algorithm is created to predict the chance that drugs will be found at a certain location. It requires five different variables in order to produce a result, and three of these data points are particularized with respect to the suspect's observed behavior. None of these data points are related, either directly or indirectly, to race, religion, or any other protected class. Assume that a police officer has personal knowledge of all of these factors and inputs them into the software, which predicts a 75% chance that drugs will be found at the location. Given these facts, a court will almost certainly find that probable cause exists and a search warrant should be issued.

How would the model work if the police officer does not have any personal knowledge about the case, and instead her affidavit quotes an informant who provides the information about all five

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270. Reasonable suspicion requires "specific and articulable facts." *Terry*, 392 U.S. at 21. Probable cause requires "facts and circumstances within their [the arresting officers'] knowledge." Draper v. United States, 358 U.S. 307, 313 (1959) (quoting Carroll v. United States, 267 U.S. 132, 162 (1925)).

variables? Once again, all five variables are entered into the software, and the algorithm predicts a 75% chance that drugs will be found at the location, assuming that the information is correct. How can the algorithm (and thus the judge) take into account the inevitable reliability questions that accompany the use of informants? In order to preserve the purely determinative model, the software must be designed so that the credibility of the informant can be taken into account as part of the algorithm. In many cases, this would be feasible. Generally, search warrant applications only have a few different categories of informants: known informants who have provided accurate information in the past, known informants who have never provided information before, anonymous informants, etc. Thus, these specific categories could be inputs into the software, so that after each relevant factor is entered, the algorithm would ask about the source of the fact—did it come from personal observation by the affiant police officer or from an informant; and if from an informant, how much is known about the informant and his prior track record?[271] These categories would be at least as specific as the descriptions currently used by police officers in search warrant affidavits.

Any outcome determinative model in this context will require a far more sophisticated algorithm, with many more potential inputs for the different behaviors that might be observed. And in designing these algorithms, the programmers will need to stay away from the vague factors that currently cause so much unreliability and are open to abuse, such as "furtive movements" or "acting suspiciously."[272] Other inputs, such as "suspicious bulge" or "nervous behavior," which could conceivably refer to specific facts that indicate the presence of criminal activity, may need to be defined with more specific language. And the inputs need to include potentially exculpatory information as well, in order to ensure that the algorithm complies with the "totality of the circumstances" requirement of the probable cause determination.[273]

Given these practical problems, it is unlikely that any predictive algorithm could ever be designed that contains every possible type of specific behavior that a police officer might use in making a reasonable suspicion or probable cause determination. Some predictive algorithms could be designed in certain basic, often-

271. *See* Goldberg, *supra* note 148, at 800.
272. *See supra* notes 58-59 and accompanying text.
273. *See* Ferguson, *supra* note 12, at 392.

repeated scenarios (observations made of individuals exiting buildings where drugs are being sold, observations made during routine traffic stops, etc.),[274] but the potential range of observed activity is simply too broad to conceive of a world in which every possible relevant factor is accounted for in the computer programming. And in some cases the police officer or judge may have her own opinion about the reliability of an informant that is not accurately captured by the five or six traditional categories that are part of the algorithm's inputs. Furthermore, it may be politically unacceptable to take human beings completely out of the loop, since this would require police officers and judges to ignore information (whether inculpatory or exculpatory) that is highly probative to the reasonable suspicion/probable cause determination.

Thus, there will be some situations in which the predictive algorithm is merely one of the factors that the judge considers. In these cases, the judge will need to incorporate the conclusions of the predictive algorithm alongside other factors. We will call these "independent" factors to indicate that they are above and beyond the factors used by the algorithm. For example, assume that the algorithm uses five different inputs and predicts a 25% likelihood that drugs will be found at a given location. The judge also knows about three independent factors that on their own do not quite rise to the level of probable cause. The judge will be provided with the 25% prediction by the software. If the predictive algorithm is meant to be one of the many factors that she considers, she would then need to combine the 25% from the algorithm and the unquantified "almost-but-not-quite" factors from her own judgment. How does she balance the specific number from the algorithm with her own intuitive conclusion? Does she have to quantify her "almost-but-not-quite" conclusion? Assume she can do this (and presumably judges would get better at this task with practice), and she quantifies her subjective conclusion at a 30% likelihood. How much weight does she give to her 30% compared to the 25% from the algorithm?

In order to accurately combine the results from the predictive algorithm with other factors, we need to take two steps. First, in order to avoid double counting, we need to separate the factors that have already been considered by the algorithm from the factors that have not.[275] The transparency that we already require from these algorithms should make this task easier; the decision-maker will be

274. *Id.* at 406.
275. *See* Goldberg, *supra* note 148, at 833.

able to review the factors that have already been considered by the algorithm and then remove those from her own independent analysis.

Second, the decision-maker must use the predictive algorithm as the starting point and then adjust the percentage chance up or down as she adds in the independent factors. One method of doing this is to apply Bayes' theorem, which is a process of combining known probabilities with new evidence in order to create a new, updated probability.[276] The predictive algorithm would provide the decision-maker with a base rate or prior probability that criminal activity is present, and then the decision-maker would apply the probability of criminal activity based on the relevant evidence that was not considered by the predictive algorithm (known as the "current probability").[277] This extra evidence could include personal observations on the part of the police officer (assuming those observations were not taken into account by the algorithm already) or extra information about the reliability of the informant that was not accounted for by the algorithm.

As an example, let's return to the modern-day version of Detective McFadden and John Terry.[278] We know from our algorithm (based only on background information about John Terry) that there is a 5% chance that Terry is carrying an illegal weapon at

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276. For an example of Bayes's theorem being applied in a legal context, see Jonathan J. Koehler & Daniel N. Shaviro, *Veridical Verdicts: Increasing Verdict Accuracy Through the Use of Overtly Probabilistic Evidence and Methods*, 75 CORNELL L. REV. 247, 255-56 (1990).

277. Bayes' theorem can be expressed mathematically as: $P = xy/[xy + z(1-x)]$. *Id.* P is the number we are trying to calculate, known as the "posterior probability"—that is, the updated probability that a certain fact is true; in this case, it is the odds that criminal activity is occurring or that contraband will be found if the search is conducted. x is the "prior probability"—the probability that a certain fact is true before the extra information is added; in this case, the odds of criminal activity or contraband that are calculated by the predictive algorithm based on all the factors that it takes into consideration. y is the probability that if the fact is true, then the extra information will be present; in this case, the odds that the independent pieces of information not considered by the algorithm exist because the defendant is engaged in criminal activity or contraband is present. And z is the probability that the fact is not true given the extra information; in this case, the chance that given that all the independent pieces of information are true, there is no criminal activity or contraband (i.e., there is a perfectly innocent explanation for all of the independent pieces of information). Obviously the decision-maker will have to estimate y and z, but this is not too different from what police officers and judges already do—only in this case they will have a much more accurate base rate to start from.

278. *See supra* note 265 and accompanying text; Ferguson, *supra* note 12, at 377-79.

any given time. Detective McFadden then observes him pacing, looking, and conferring and realizes this is exactly the kind of behavior that he would expect a potential robber to engage in before committing the crime.[279] Thus, Detective McFadden estimates that a person who is planning a robbery is 90% likely to engage in the kind of behavior that Terry is currently engaging in. And although the detective realizes that there are some innocent explanations for this kind of behavior (perhaps Terry is window shopping and then conferring with his friend about what to buy), the fact that Terry has repeated this behavior multiple times means that the odds of him not planning a robbery are only about 10%. Given these estimates, the detective can complete a Bayesian calculation (or, more likely, input these estimates into a simple calculator that will then conduct the Bayesian calculation) and determine that the chances that Terry is engaged in criminal activity are 32.1%.[280] Assuming that courts set the standard for reasonable suspicion at around 20% to 25%, this would be sufficient to establish reasonable suspicion.

In contrast, assume that our modern Detective McFadden, like the real-life Detective McFadden, did not have any information about John Terry's background. Instead, he merely observed Terry's suspicious behavior. Under Bayes' theorem, our base rate would be much lower. Perhaps we recognize that this is a high crime neighborhood, so we know that 1% of the population is carrying an illegal weapon at any given time. If Detective McFadden makes the same observations as before and he calculates the same odds of criminal activity based on those observations, the chances that Terry is engaged in criminal activity drops to only 8.3%.[281] In other words, the lower base rate from the lack of big data makes the detective's prediction of criminal activity much less accurate.

Thus, even if predictive algorithms are not outcome determinative, using a more statistical approach to determine reasonable suspicion or probable cause will allow police officers and judges to incorporate more reliable base rates into their calculations. Predictive algorithms will also help these decision-makers avoid a

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279. Some robbers might simply barge in without investigating the location first, but most robbers would want to take a good look at the location, looking to see how many people are present, where the cash register or other valuables are kept, and (in the modern age) whether there are any security cameras inside. *See* Ferguson, *supra* note 12, at 378.

280. Applying Bayes' theorem: $P = .05*.9/[.05*.9 + .1*(1-.05)] = .321$.

281. Again, applying Bayes' theorem: $P = .01*.9/[.01*.9 + .1*(1-.01)] = .043$.

common problem when making predictions: ignoring or undervaluing the base rate. As can be seen from our above example, a very low base rate or prior probability for potential criminal activity means that even very suspicious independent factors might not result in a very high resulting probability. Studies have shown that individuals who make predictions frequently undervalue or even ignore base rates and give too much weight to the independent factors that they are presented with.[282] Forcing police officers and judges to incorporate the base rate in making their calculations would be another benefit of using a quantified system of criminal procedure.

Of course, the more we allow the decision-makers to use independent factors, the more we lose the benefits of predictive algorithms, such as the increased accuracy and the mitigation of subjective and potentially biased human input. For example, when Detective McFadden enters in his own probability estimates into the Bayesian calculation, he may underestimate the chance that Terry has an innocent explanation for his conduct because Terry is African-American, and the detective has an irrational implicit bias against African-Americans. This would result in a higher prediction of criminal activity for Terry than it would for a white person with the same background engaging in the same activity. Thus, we should design our algorithms to avoid the need for independent factors as much as possible, since the biases in the algorithms can be detected and minimized.

CONCLUSION

Big data's predictive algorithms have the potential to revolutionize the way police investigate crime and the way the courts regulate the police. For centuries, courts have been crafting legal standards for police officers who were making clinical judgments based on experience and intuition. The imprecision and subjectivity of these legal standards were a necessary evil—they were required given the subjective factors that were used by the police, but their accuracy could not be tested, they made the system less transparent, and they opened the door to vastly inconsistent and frequently discriminatory results. With the rise of big data's predictive algorithms, we have an opportunity to increase the accuracy and the transparency of the way we apply the standards and of the standards

282. Koehler & Shaviro, *supra* note 276, at 256.

themselves, making the system more efficient, more fair, and more open.

In order to reap these benefits, we need to ensure that the predictive algorithms are race neutral and that they take into account individual suspicion. This may require new types of algorithms that are specifically designed for determining reasonable suspicion and probable cause. It will certainly require that the algorithms be transparent, so that reviewing courts can understand what factors the algorithm is using. More controversially, we need to update the definition of reasonable suspicion and probable cause to include quantifiable standards. Although courts have shown a strong aversion quantifying standards in the past, the benefits to such a change far outweigh the costs. We have seen that some courts, recognizing this fact, have already started to experiment with using quantified standards when evaluating some of the factors put forward by law enforcement officers or when evaluating the tools that these officers use in determining probable cause.

To be sure, a system of mechanical predictive algorithms and quantified legal standards will not be perfect. It will probably be impossible to scrub all residue of racial discrimination from the existing databases, and police officers and judges will almost certainly make mistakes when trying to use the predictive algorithms as base rates and then adding their own independent observations. And the predictive algorithms themselves will still make mistakes, and thus will not always be as accurate as we would like. But the current system includes the implicit and sometimes explicit biases of police officers and judges; vague standards that can be manipulated by police officers, which are more or less incomprehensible to lay people; and accuracy rates (when they can be measured) that vary wildly from jurisdiction to jurisdiction. The time has come for courts to embrace the enhanced precision and transparency that big data has to offer.