The Hidden Inconsistencies Introduced by Predictive Algorithms in Judicial Decision Making

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Abstract
Algorithms, from simple automation to machine learning, have been introduced into judicial contexts to ostensibly increase the consistency and efficiency of legal decision making. In this paper, we describe four types of inconsistencies introduced by risk prediction algorithms. These inconsistencies threaten to violate the principle of treating similar cases similarly and often arise from the need to operationalize legal concepts and human behavior into specific measures that enable the building and evaluation of predictive algorithms. These inconsistencies, however, are likely to be hidden from their end-users: judges, parole officers, lawyers, and other decision-makers. We describe the inconsistencies, their sources, and propose various possible indicators and solutions. We also consider the issue of inconsistencies due to the use of algorithms in light of current trends towards more autonomous algorithms and less human-understandable behavioral big data. We conclude by discussing judges and lawyers’ duties of technological (“algorithmic”) competence and call for greater alignment between the evaluation of predictive algorithms and corresponding judicial goals.

1 Introduction
Prediction and classification methods have played a role in judicial decision making for over a century. For nearly just as long, questions about the suitability and performance of such methods have loomed. In 1895, for instance, Francis Galton wondered whether different judges might impose different patterns of penalties for the same kinds of offenders (Gottfredson, 1987). What started as “behavioral forecasts” informing parole decisions in the 1920s (Berk and Bleich, 2014) eventually evolved into more sophisticated “actuarial” prediction methods used since at least the 1970s in the United States (US). Since then, statistical prediction methods have been used in a variety of criminal justice contexts including sentencing, pretrial incarceration, parole, probation supervision levels, and security levels decisions in the US (Brennan, 1987). More recently, growth in the digitization of court records, data collection, and cheaper processing power has catalyzed the use of data analytics and algorithms in the decision-making processes of law enforcement agencies, corrections officials, and judges (Coglianese and Ben Dor, 2020; Crawford and Schultz, 2014).

According to experts, this trend turns on two interrelated factors: efficiency and consistency (Gertner, 2010). Firstly, the data-driven approach represents a cost-effective solution, aiding criminal justice officials in prioritizing government resources and in predicting and controlling complex individual behaviors. Secondly, consistency in judicial decision-making is not only a key tenet of the rule of law (Finnis, 2011, p. 270) but also crucial to the perceived legitimacy of sentences (Roberts and Hough, 2005). Proponents argue big data analytics promises to reduce human bias and provide a scientific and
evidence-based approach to the judicial process (Simmons, 2018; Završnik, 2020). The goal is to move the US towards a “smarter” regime by incorporating statistical and machine learning (ML) risk prediction algorithms into the decision-making processes of judges (Berk and Hyatt, 2015). For instance, ML is now increasingly used to predict the likelihood of the recidivism or flight of those awaiting trial or offenders in bail and parole procedures (Završnik, 2019).

While these new techniques may be useful in the judicial context, experts disagree about their appropriateness. Some scholars see the algorithmization of the judicial decision-making roles as inevitable and argue courts should embrace automation to better serve their mandates (Volokh, 2018). Others, however, argue ML may inadvertently reflect and exacerbate existing biases and discrimination embedded in training data (Liu et al., 2019). Still others call for applying well-designed (even if imperfect) algorithms as a way to counter human judges’ biases and inconsistencies, thereby improving the criminal justice system (Corbett-Davies et al., 2017).

This paper argues an additional, hidden layer of inconsistencies may emerge due to the way algorithmic tools are designed, employed, and communicated. Left unchecked, these inconsistencies contradict the underlying rationale of applying algorithmic tools in the judicial context—namely, bringing evidence-based, algorithmic “consistency” to the human-centered, error-prone judiciary. On the basis of these issues, we claim judicial consistency, broadly defined here as treating similar cases similarly (Brantingham, 1985; Pina-Sánchez, 2015), can be compromised, thus warranting caution when adopting algorithmic tools. Further, the move to applying not only hard-coded rules and statistical models, but also black box machine learning algorithms—such as Deep Learning—to the court system, could exacerbate these problems (Bathaee, 2017; Deeks, 2019; Pasquale, 2015). As ever-more fine-grained behavioral big data are used to algorithmically generate predictions in legal settings, we must consider what this might mean for the future of the judiciary. One issue concerns the admissibility of certain kinds of statistical evidence as applied to the cases of individual persons.

Scope and Structure of Paper
This paper mainly refers to US examples and may not appear generalizable to other legal contexts in Europe, Asia, or elsewhere. But we focus on the US for a number of reasons. To start, the US has a long history of using risk assessment in its criminal justice system (Monahan and Skeem, 2016). Further, the US is a highly-litigious society (Greenhouse, 1989), and judges are continually seeking solutions for managing their dockets. Finally, the US incarceration rate is higher than any other major country in the world: the US makes up less than 5% of the world’s population, but accounts for over 23% of the world’s incarcerated people (Hartney, 2010). Consequently, given the scale of incarceration and its associated costs, success in predicting recidivism or cases of “failure to appear” in court can become a legitimate fiscal issue for cities and states (Kleinberg et al., 2018). Nevertheless, as ML-based technology and data collection tools improve in their ease of use, cost-efficiency, and sophistication, our work is poised to apply beyond the US. As a case in point, many countries beyond the US are implementing, e.g., China (Li, 2020) and the United Kingdom (Cui, 2020,
Against this backdrop, the present article is aimed at a general audience and adds to these discussions by examining hidden inconsistencies introduced by predictive algorithms in judicial decision-making contexts. While earlier research on ML in the judicial context has focused on two aspects of algorithmic explanation, namely inscrutability and non-intuitiveness (Selbst and Barocas, 2018), our focus is more general. We identify four hidden inconsistencies applicable to risk prediction algorithms—beyond inconsistencies in different statistical fairness criteria (Courtland, 2018)—that apply to data collection and algorithmic training, testing, and finally deployment stages. We are concerned with showing how these algorithmic tools are often built using assumptions end-users may not be aware of. Ideally, lawyers, judicial decision makers, and other users of such tools should be capable of asking incisive questions about the design and evaluation of such systems. Likewise, data scientists and data engineers should understand how these systems are used in legal contexts and what the legal implications of their data science decisions may be. One widely-applicable conclusion is that the goals and objectives of algorithmic prediction must be carefully aligned with legal/social objectives and applications. This will require greater coordination and cooperation between data scientists, legal professionals, and domain experts.

The paper is structured as follows. Section 2 describes each inconsistency and provides a brief discussion of indicators and potential solutions. Section 3 considers future inconsistencies following the trend of using more complex algorithms and behavioral big data. Section 4 outlines the basis of judges’ and lawyers’ duties of technological (“algorithmic”) competence and its potential to influence the alignment and development of predictive algorithms and corresponding judicial goals.

2 Inconsistencies Introduced by Algorithms
Algorithmic2 risk prediction models introduce new inconsistencies into judicial decision-making, yet judges, lawyers, and defendants may be unaware of their impact. Judicial decision-making is the process of how judges come to a solution for a given issue through legal reasoning, interpretation, and application based on the relevant laws, regulations, precedents, facts as well as the guiding values and policy orientations of the judges (Capurso, 1999; Ellsworth, 2005). In the context of sentencing, judicial decision-making is often concerned with assessing an individual’s likelihood of future unlawful behavior, given their unique personal characteristics, social connections, and past history (Monahan and Skeem, 2016). Such assessments are conducted at numerous stages in the judicial process and are increasingly supported by algorithms and AI (McKay, 2020). Ideally, sentencing and treatment determinations are made in order to minimize the probability of future unlawful behavior (Hamilton, 2015). These decisions, however, are unlike those found in natural science contexts, where outcomes of interest can be objectively determined and procedures for achieving them can be mathematically formalized and

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1 France, however, moved to ban machine learning and AI from the courtroom and penalize the use of public court data in predictive algorithms (ABA Journal, 2019).

2 Algorithms can be thought of as “specific procedures used to implement a particular data mining technique” (Shmueli et al., 2017, p. 9), such as logistic regression, classification trees, and neural networks, etc.
optimized. In predictive decision-making scenarios faced by judges, for example, the operationalization of legal concepts such as recidivism is not straightforward and a variety of measures are equally valid (Zamble and Quinsey, 1997).

Several of these inconsistencies arise not from the final application of the algorithms themselves, but rather from the human elements involved earlier in the data gathering, cleaning, and variable selection phases. Human factors include the data subjects, data collectors, data scientists, and other human decision makers. Gelman and Loken (2014), for instance, refer to these kinds of data analysis decisions as a “garden of forking paths” and to variable human factors as “researcher degrees of freedom.” In practice, critical choices must be made by data scientists developing the algorithmic system. Perhaps the most important and challenging task they face is in navigating between *fuzzy* legal and behavioral concepts, and *precise* measurable data and mathematical quantities (Barocas et al., 2019; Selbst and Barocas, 2018). Table 1 summarizes the human elements involved in each of the four inconsistencies.

Table 1. Human elements involved in each of the inconsistencies.

| Inconsistency in…                      | Human Elements                                      |
|---------------------------------------|----------------------------------------------------|
| Choice of Measured Outcome/Predictors | Data Scientists, Data Engineers                    |
| Choice and Quality of Training Dataset| Data Scientists, Data Subjects, Data Collectors    |
| Predictive Accuracies of Subgroups    | Data Scientists, Data Subjects, Data Collectors    |
| Communicated Risk Scores              | Data Scientists, Judicial Decision makers           |

2.1 Choice of Measured Outcome and Predictors

The fluid nature of legal concepts is often at odds with the data-specific requirements of statistical and machine learning algorithms. The performance of a predictive model heavily depends on the choice of the measurement designated as “outcome to predict.” Designing a predictive model entails searching for an algorithm that best predicts that measurement for new individuals. Hence, different choices of an outcome measurement can introduce dramatic inconsistencies in predicted scores. In their examination of bias in predictive algorithms, Barocas and Selbst (2016) warn, “danger resides in the definition of the class label itself and the subsequent labeling of examples from which rules are inferred.” In other words, legal labels such as “violent” or “low-risk” can be operationalized in a variety of ways, each way leading to different predictions.

Challenges in Defining Recidivism

Surprisingly, there is no generally accepted legal definition of “recidivism” (Zgoba and Dayal, 2016), and the literature devoted to discussing, defining, and approximating various operationalizations of recidivism have a long history (e.g., Blumstein and Larson, 1971; Rector, 1958). Some define it as the duration between two events, e.g., days from release date to the point of the first warrant date (Breitenbach et al., 2010). Others measure it by a dichotomous “reconvicted/not” or “new arrest/not” within a certain time period from some
event (Jones and Sims, 1997; Maxfield, 2004). A Bureau of Justice Statistics (2002) report uses four measures of recidivism: rearrest, reconviction, resentence to prison, and return to prison with or without a new sentence within a three-year period following the prisoners’ release, and further distinguishes between “in-state” and “out-of-state” recidivism. The much-publicized ProPublica study of bias in risk assessment tools defined it as a new arrest within two years of the original crime for which the subject was assessed, while discounting any minor offenses and municipal ordinance violations (Larson et al., 2016). However, this definition is problematic because it counts subjects who were arrested but were not convicted, and those whose charges were dropped. The choice of recidivism measure also leads to different selected models and algorithms: predicting the expected time until recidivating calls for a different type of model than for the probability of recidivating in the next five years. The same model cannot produce both.

In sum, the existing definitions commonly share three features. Each definition has a starting event from which the measurement of recidivism commences, e.g., release from prison. Second, each definition has a measure of failure following the starting event, e.g., a subsequent arrest. Third, each definition has a window of recidivism, that is a follow-up period within which the offender’s behavior is examined (Zgoba and Dayal, 2016).

Table 2. Various criteria used to measure recidivism.

| Criteria                      | Options used by different studies/systems |
|-------------------------------|------------------------------------------|
| Events                        | Arrest, Conviction, Incarceration         |
| Degree                        | Felony, Misdemeanor, Public Ordinance    |
| Time Periods                  | 2 Years, 3 Years, 5 Years, …              |
| Since                         | Previous Crime, Arrest, Incarceration, Conviction |
| Inclusion Criteria            | In-state/Out-of-state                    |
| Predicted Outcome Type        | Time-to-recidivate, Probability of Recidivism, Hazard Ratio |

Note. Definitions obtained from Blumstein and Larson (1971); Breitenbach et al. (2010); Bureau of Justice Statistics (2002); Jones and Sims (1997); Larson et al. (2016); Maxfield (2004).

Changing the time horizon in the definition of recidivism dramatically changes the base rate\(^3\) of the phenomenon, which in turn affects relevant predictive performance measures. For example, Rice and Harris (1995) show changes in the definition of “violent recidivism” to include any new violent crimes within a horizon of 3.5, 6, and 10 years (resulting in base rates of 15%, 31%, and 43%, respectively), causes various performance measures of the Violent Risk Appraisal Guide (VRAG) model to fluctuate dramatically. Nevertheless, end users of predictive tools may not know which definition of violent recidivism was used in the final model. A judge might incorporate the VRAG’s risk

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\(^3\) The base rate of a phenomenon refers to its underlying proportion in the population of interest (e.g., “5% of all male prisoners recidivate within five years of release.”)
assessment score in passing down a sentence, assuming the score reflects the defendant’s risk of recidivating within the next two years, when in fact it actually reflects a ten-year risk.

Model Selection and the Reference Class Problem
A second source of inconsistency arises due to selecting predictors—the measures used as inputs into the predictive algorithm, which are assumed to be predictive of the outcome. Developing robust predictive models requires trading off model complexity with model fit (the so-called “bias-variance tradeoff”) (Hastie et al., 2008p. 219). An overly-complex model containing many predictors can be made to fit arbitrarily well to a given dataset, but in doing so loses the ability to predict well for new, unseen data. The model is said to be “overfit,” essentially memorizing the distribution of the training data including its inherent noise (Kuhn and Johnson, p. 62). To combat this, a key data science strategy is the process of “model selection” (Hastie et al., 2008, p. 38). The goal of this process is to achieve an optimal balance between model complexity and fit, effectively detecting just the predictive signal in the training data and discarding noise. The generalization performance of the resulting model is typically indicated by the classification error on a test set of data not used to fit the model. Smaller test set error is taken to indicate better generalization ability.

Interestingly, Cheng (2009) argues model selection is analogous to the “reference class problem” in legal risk-assessment. This is because the predictors included and excluded in the final model determine the criteria potentially defining one’s reference group. The more predictors selected, the narrower the potential scope of an individual’s reference group used to calculate his risk. For example, we can calculate risk based on gender alone, or on a larger set of predictors such as gender, age, and zip code. In the former, the reference class is other people of the same gender, whereas in the latter the reference class is others of the same gender, age, and in the same zip code. Hájek (2007) explains the reference class problem arises “when we want to assign a probability to a single proposition, X, which may be classified in various ways, yet its probability can change depending on how it is classified.” This is problematic because risk models often rely on an interpretation of probability as limiting relative frequency, such that the probability of events or attributes can only be assessed “within the given collective” (von Mises, 1957 p. 15). On this interpretation, truly unique, singular events do not have probabilities.

Unfortunately, there is no simple data science solution for deciding an individual's most relevant reference class. In contrast to the masses of identical particles studied in the natural sciences, humans are uniquely self-interpreting animals (Taylor, 1971). Humans can react to and in some cases vehemently deny the labels ascribed to them. They can live only one actual life, not infinitely many, as the frequentist account of probability above imagines. Remark on these and further limitations of statistical learning theory as applied to the human social context, Cherkassky and Mulier (1999, p. 59) warn:

It is also important to bear in mind that in the formulation of a learning problem, unknown distributions (dependencies) are fixed (or stationary). This assumption usually holds in physical systems, where the nature of dependencies does not depend on the observer’s knowledge about the system. However, social systems strongly depend on the beliefs of human
observers who also participate in the system's operation. The future behavior of the social systems can be affected by the participants’ decisions based on the predictive models. Hence, *the framework of predictive learning, strictly speaking, cannot be applied to social systems.* (italics ours)

So determining an individual person’s reference class, for better or worse, remains a philosophical and legal issue. The 1995 case of *United States v. Shonubi* provides a vivid example of the difficulties involved in what, on the surface, appear to be straightforward questions of probability. Tasked with estimating the unknown amount of heroin Mr. Shonubi—a Nigerian national and US resident—smuggled into JFK on seven previously undetected trips, Cheng (2009) says, “The court could have considered the amount carried by all drug smugglers at JFK, all Nigerian smugglers regardless of airport, or smugglers in general.” Each reference class assignment would result in different estimates. The accuracy of these estimates was important because they effectively decided which sentencing guidelines would be applied to his case. The ensuing legal battles eventually resulted in a heated academic discussion of when exactly statistical evidence is admissible as “specific evidence” to be used in an individual’s sentencing proceedings (Tillers, 2005).

The upshot of the above discussion is simply that, due to a confluence of the reference class problem and the model selection process, inconsistencies are created between and across individuals and model classes that rely on different sets of predictors. The most predictively accurate model for predicting Parolee A’s recidivism might exclude predictors legally relevant in predicting Parolee B, who rightfully belongs to a different set of reference classes (e.g., the set of *all drug smugglers at JFK* or the set of *all Nigerian drug smugglers between the years 2000-2005*). Prior choices of which data to collect will determine which predictors, and therefore which reference classes, can result after the model selection process. Tiller (2005) concludes there is “no meaningful way of limiting the reach of the specific evidence requirement to statistics and statistical argument.” All of this is to say the model selection process and the reference class problem add potential sources of inconsistency into judging risk, both between and across individuals.

Finally, data scientists may add inconsistency when attempting to improve model performance. For example, an outcome measure including rare crimes might create an unbalanced dataset that is difficult to model; the data scientists might thus group together the set of rare crimes. In this vein, the judicial decision support system used in Multnomah County, Oregon advises judges to increase the breadth of crimes, age, and even gender in order to collect enough “similar” cases that can be used. 4 Breitenbach et al. (2010, p. 236) conclude, “the performance of any instrument will vary depending on the population (e.g., prison releases or probation cases), measurement error in the scale or outcome, and type of outcome (e.g., arrests versus violations or returns).” For example, for “violent” felony crimes, a crude dichotomous outcome measure hides important causal distinctions (drug-related vs. domestic violence) and leads to inconsistent risk predictions not appropriately linked to the context of the individual under assessment (Breitenbach et al., 2010).

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4 Multnomah County Decision Support System-Justice Review (2016):
https://multco.us/file/62265/download
Potential Indicators and Solutions
Ideally, there should be agreed-upon legal definitions of terms such as recidivism, and what constitute valid and reliable measures. The field of psychometrics can provide scientific guidelines as to constructing and evaluating suitable measures. Identifying inconsistencies due to various outcome measures requires transparency by system designers, as well as sensitivity analyses when using alternative measures. The data science approach of ensembles (averaging multiple models) with different recidivism measures is another possibility for enhancing consistency, although how to ensemble such different models is not straightforward. For model selection, sensitivity analysis and ensembles may again be useful approaches. Another approach empowers judges as users: some systems (e.g., the Oregon state judicial support systems) allow the interactive selection of a relevant reference class, effectively allowing manual model selection for each individual case.

2.2 Choice and Quality of Dataset Used to Train the Algorithm
Algorithmic decision-making tools range in their reliance on data for developing the algorithm (Surden, 2018). At one extreme, hard-coded rules, such as “exceeding the speed limit by over 10% leads to a $100 fine,” require no data. On the other extreme, autonomous machine learning algorithms, such as those used in recommendation systems or deep learning algorithms, learn the entire structure between input and output from data they were trained on. Most predictive models used in judicial contexts, however, currently occupy a middle ground based primarily on the use of so-called “4G” statistical modeling approaches to correctional assessment (Brennan et al., 2008). COMPAS risk classification, for example, relies on logistic regression, survival analysis, and bootstrap classification methods (ibid.).

Imbalanced data, Measurement Error, and Selection Bias
Nevertheless, developing models at this level still requires many non-trivial choices by data scientists, such as which phenomena are of interest to study and how best to measure or aggregate them. For example, when dealing with highly imbalanced datasets, a simple but under-used approach is to redefine the problem and “find a subdomain where the data is less imbalanced, but where the subdomain is still of sufficient interest” (Weiss, 2013). For example, restricting the population modeled to only those with prior criminal history or those committing violent crimes. Doing this however, takes considerable legal knowledge. Nevertheless, these choices may result in different training datasets and therefore different predictive models. Hence, when using a dataset to train an algorithm used to predict new people’s behaviors, measurement error and selection bias can lead to inconsistencies in resulting scores. Measurement error can occur “whenever we cannot exactly observe one or more of the variables that enter into a model of interest” (Buonaccorsi, 2010, p. 1). Selection bias, on the other hand, is a concern when relying on non-randomly selected samples to estimate relationships among predictors in a model (Heckman, 1979).

Datasets used for training and evaluating a model’s predictive power must include the outcome measure of interest as well as a set of relevant input measures. These inputs and outcomes are linked through an algorithm to form a predictive relationship. For recidivism,

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5 An imbalanced dataset is one where one of the outcome classes (e.g., “recidivate”) is a small minority compared to the other class (e.g. “non-recidivate”).
data on offenders’ arrests are needed. These data, however, suffer from noisy measurement and can even be intentionally-manipulated either by the data subjects or by the data collectors. Plea-bargains, for example, introduce noise when a person is arrested for one crime but ultimately charged for another, less serious one (Breitenbach et al., 2010). As another example, pre-parole questionnaires are used in risk assessment systems in the Pennsylvania Corrections Department (Barry-Jester et al., 2015). Specifically, Pennsylvania’s parolees are asked simple yes/no questions regarding their past behaviors (e.g. whether they have ever had a drug or alcohol problem). But they are not asked to indicate the severity of the problem or what exactly constitutes a “drug or alcohol problem.”

Measurement error can arise also due to manipulation of human data collectors through financial incentives. Organizational pay-for-performance schemes may motivate police to incorrectly classify crimes and describe arrests (Muller 2018, p. 128). Such gaming techniques used by police to “hit their targets” include: a) “choosing not to believe complainants,” b) “recording multiple incidents in the same area as a single crime,” and c) “downgrading incidents to less serious crimes.” Maltz (1999) also mentions the decades old FBI hierarchy rule for ensuring that crimes would not be double counted. The rule states that when two different types of crime occur in the same incident, only the category of the most serious crime is counted (ibid., p. 14): “If a convenience store robbery results in the death of the store clerk, this would be classified as a homicide rather than a robbery—because homicide is a more serious crime than robbery.” Such gaming strategies and arbitrary operating procedures lead algorithms to learn relationships more reflective of record-keeping limitations and wishful thinking than of reality.

As mentioned earlier, datasets used to train and test predictive algorithms for use in criminal law can suffer from over-representation of some populations and under-representation of other populations (Završnik, 2019). Such misrepresentation leads to inconsistencies when deployed to new members of under-represented populations, or even to completely different populations. A salient example of this problem is when predictive models largely trained on male inmates are applied to female inmates (Hannah-Moffat and Shaw, 2001). Systems developed and trained for one application are now used not only for new populations (geographically, demographically, temporally, etc.), but also in unintended contexts, such as an algorithm developed for decision on prison releases being applied for probation decisions (Kehl and Kessler, 2017). For example, the Public Safety Assessment tool used pre-trial training data from 300 US jurisdictions, but was applied statewide in Kentucky, Arizona, New Jersey, and Utah, where pre-trial populations of ethnic subgroups are likely different from the overall population of jurisdictions (Stanford Law School Policy Lab, 2019a).

Data collection mechanisms are one cause of such misrepresentation. For example, approximately 10% of randomly-selected inmates declined to participate in the data collection efforts for the COMPAS Reentry risk assessment tool (Breitenbach et al., 2010). Combining these data with arrest data generated by predictive policing algorithms introduces a further selection bias: research has shown that increased police surveillance leads to more arrests and recorded criminal incidents (e.g., Na and Gottfredson, 2013). When such data are then fed into judicial decision making algorithms, they create a self-sustaining feedback loop that reflects more the nature of the crime sampling process than actual patterns of criminal
behavior (Partnership on AI, 2019). In addition, data preparation decisions can lead to selection bias, for example, by removing records with missing values. When such missingness is systematic (e.g. refusal to respond to sensitive questions about criminal behavior), it leads to the exclusion of specific populations.

**Potential Indicators and Solutions**
Identifying and tackling measurement error requires transparency and knowledge about data collection practices and mechanisms for testing data quality. For instance, the Stanford Pretrial Risk Assessment Tools Factsheet Project (Stanford Law School Policy Lab, 2019b) audits several pre-trial risk prediction tools, providing details about the training and testing data used, predictive performance in terms of AUC, and other important factors such as which jurisdictions use it and whether its users must undergo prior training. To identify selection bias, an algorithm’s performance should be evaluated in a context as close as possible to the one in which it will be deployed, instead of relying on generic AUC values. There are some reports of such testing, especially in new geographical regions: NorthPointe reported testing COMPAS across multiple jurisdictions and state agencies (Breitenbach et al., 2010; Brennan et al., 2008). Likewise, Tollenaar and van der Heijden (2019) trained algorithms on Dutch conviction data and subsequently tested them on North Carolina prison data. For predictive models trained using oversampling or undersampling of rare or overrepresented classes (e.g., women in COMPAS Reentry), it is especially important to assess predictive performance in a context as close as possible to the deployment context.

**2.3 Predictive Accuracy and Precision for Different Subgroups**
No matter the algorithm used, some individual or group-level records are harder to predict than others, resulting in larger prediction errors. Our notion of inconsistency reflects a similar problem. Highly uncertain cases should not be treated the same as more certain cases, yet many current systems fail to indicate this.

**Predictor Information and Tradeoffs in Fairness and Accuracy**
One factor affecting such differences in prediction errors is the amount of data collected on some subgroups relative to others. Another factor concerns predictor information that might have more predictive power for some subgroups compared to others. For example, the predictor “criminal history” might be more predictive of recidivism for older defendants than for younger ones without a detailed criminal history. As the U.S. Sentencing Commission (2017, p. 2) notes, “an individual offender’s criminal record cannot decrease with age, only stay constant or increase.” Yet algorithms will always produce a predicted score, and the predicted score will not convey this inconsistency in predictive power.

In the machine learning literature, the idea that false positive rates should be relatively balanced across protected classes of persons (e.g., race) is called “equal opportunity” (Hardt et al., 2016). We note, however, that “equal opportunity” may be “statistically impossible to reconcile if there are differences across two groups—such as the rates at which white and black people are being rearrested” (Courtland, 2018). Further, detecting unequal predictive

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6 AUC, or “Area Under the (ROC) Curve” of a predictive algorithm, estimates the probability that a random positive observation (e.g. recidivator) ranks higher than a random negative (non-recidivator) (Flach, 2019).
accuracy in subgroups requires access to and basic knowledge of performance metrics. Judges without training in ML are thus likely to be unaware of such disparities across subgroups. Even when ML algorithms are optimized according to mathematical definitions of fairness, tradeoffs between fairness and predictive accuracy must always be made (Berk et al., 2018). Several potential models may achieve an “optimal” balance of fairness and accuracy, but eventually a human decision-maker must select the “best” tradeoff among these competing models.

**Potential Indicators and Solutions**
Identifying different levels of predicted accuracy for different subgroups can happen at the performance evaluation stage or a later auditing stage with access to testing data. The Partnership on AI (2019) recommends reporting variation along with predicted scores (e.g. “for people with these input data, the algorithm performs poorly”). These discoveries can improve the model’s ability to predict poorly-predicted subgroups. Further, ML approaches such as *boosting* can help improve predictive accuracy for “difficult-to-predict” individuals. Boosting iteratively re-weights cases in the dataset based on their prediction error and then combines the results (or “votes”) of many trained models to predict an overall classification (Hastie et al., 2009, p. 338). Nevertheless, we recommend judges exercise caution when relying on boosted predictions, as they suggest complex dependencies in the data.

**2.4 Communicated Risk Scores**
Current judicial risk prediction tools use algorithms that produce *class-based*, as opposed to *individual-based* risk probabilities. However, what is often conveyed to the end user—the judge—can be considered a *dichotomous prediction with qualified confidence risk levels* (Grasso and Appelbaum, 1992). These typically take the form of statements such as, “The defendant will commit a similar act in the future with high/medium/low risk.” Risk levels are created by tool designers by grouping probabilities into a few “risk levels” in order to “aid practitioner interpretation” (Chiappa and Isaac, 2019, p. 6). In some US states, such as Kentucky, practitioners are required to do this (Stanford Law School Policy Lab, 2019a). Converting probabilities into risk levels can increase consistency across judges who might interpret probability in different ways, but at a cost of reduced precision (i.e., validity).

On the other hand, a more precise and finer breakdown of risk levels may limit the discretion enjoyed by a judge in judicial decision-making processes. Gastwirth (1992) reports a study of judges in the Eastern District of New York revealing varying interpretations of probability assigned to important legal standards of proof, such as “preponderance” or “beyond a reasonable doubt.” Despite legal standards being phrased in probabilistic sounding terminology, they are only roughly translatable into numerical quantities. When an algorithm’s predicted probabilities are converted to risk levels, this “hidden” process is typically neither driven by legal considerations nor aligned with the specific chosen outcome (e.g., the outcome measure is not “risk level”), thereby creating an inconsistency across systems and applications.
**Decision Thresholds, Ranking, and Calibration**

In many predictive applications, probabilities are converted into dichotomous predictions by applying a “cut-off threshold,” such as at 0.50. This behavior is frequently encountered in automated decision-making systems. However, in systems aiding human decision making, access to these “raw” probabilities could allow decision makers to better integrate risk information with additional information. Ashworth and Zedner (2014, p. 133) explain that predicted probabilities “avoid the problem of false positives because they do not claim to foretell whether a given offender will or will not offend, but only to estimate a given population’s propensity for violence.” Nevertheless, there may still be a large, unaccounted for gap between a predicted probability and dichotomous prediction derived from a cut-off threshold. For example, an algorithm might classify an individual as a recidivist if her predicted probability ranges between 0.50-0.99.

Typically, the machine learning literature refers to the predictive goal of a ranked ordering of risk scores as *discrimination*, whereas estimation of an exact probability of recidivism (compared to the percentage observed in the test set) is referred to as *calibration* (Tollenaar and van der Heijden, 2019). As Fawcett (2006) explains, a predictive algorithm “need not produce accurate, calibrated probability estimates; it need only produce relative accurate scores that serve to discriminate [between] positive and negative instances.” We note that these different predictive goals can result in different predictive models, and small differences in relative ranks (e.g., 1-2) may hide large absolute differences in probability (e.g., 0.99-0.01).

**Potential Indicators and Solutions**

Algorithm training and performance must be aligned with the deployment context in a legal setting. Završnik (2019, p. 10) asks, “At what probability of recidivism should a prisoner be granted parole? Whether this threshold ought to be a 40 percent or an 80 percent risk of recidivism is an inherently ‘political’ decision based on the social, cultural and economic conditions of the given society.” For systems required to report only risk levels, model development, comparison and performance evaluation should be geared towards and calibrated for accurate prediction of those risk levels, rather than probabilities. Risk levels should be guided by legal considerations and tested in legal settings to assure proper interpretation. This is important as AUC has been criticized because it obscures the fact that a given predictive algorithm will not be used over *all possible cut-off thresholds* (Hand, 2009), but at a *specific value* ideally aligned with judicial precedent and socio-political goals. These threshold values should be communicated to end-users so they can better interpret the practical relevance of stated AUC values.

Although ML techniques are often justified by claims of cost-efficiency (Gertner, 2010), surprisingly few predictive applications use *lift* to evaluate performance (Shmueli, 2019). Lift, like AUC, measures *ranking* ability and can be thought of as the algorithm’s ability to “skim the cream” and select, from a subset of all test set individuals, as large a proportion as possible of true positive cases (e.g., persons who in fact recidivated) (Shmueli et al. 2017, p. 136). A similar approach is often taken by government agencies to investigate potential cases of tax fraud due to limited time and funding. They thus focus attention on only those predicted most likely to cheat. As a real life example, consider the Internal Revenue
Service’s (IRS) Discriminant Index Function algorithm to identify potential tax cheats. According to Harcourt (2008, p. 8), the IRS receives roughly “130 million individual tax returns per year, but only has the resources to audit about 750,000 or 0.6 percent of those filings.” The IRS would audit only those tax forms “flagged” as most likely (i.e., ranked) to be fraudulent.

As a performance measure that explicitly considers budgetary limits, lift seems well-suited for judicial and policing contexts. But lift requires greater coordination between data scientists and legal domain experts, as they would need information about budgetary constraints and operating scenarios in advance. One final note of caution: using lift requires carefully assessing whether ranking people and acting only on the top-ranked makes legal and moral sense. We can imagine situations where predicted probabilities are—in an absolute sense—low and acting on a predefined top x% of cases would violate common sense notions of fairness.

3 Discussion
We have outlined four inconsistencies created by algorithms used for risk prediction in judicial decision-making. For each, we pointed out potential indicators as well as potential solutions. These inconsistencies arise from inherent difficulties in translating legal and behavioral criteria into precise mathematical frameworks (Gastwirth, 1992) needed for predictive algorithms. Current risk models are mostly limited to statistical regression models, which are relatively interpretable and computationally stable. However, the next generation of risk models will likely rely on more autonomous, “data-driven” ML algorithms, such as those used in predictive policing. If things do move in this direction, the four hidden inconsistencies we mentioned will persist and perhaps become even more difficult to detect.

In fact, a move towards more data-driven machine learning methods may lead to additional inconsistencies. Experience with personal data in the EU (e.g., the GDPR) and complex predictive models used in the financial services industry (e.g., Basel II/III) suggests boundaries will need to be drawn regarding the appropriate level of granularity of personal data and also interpretability of machine learning methods used in the legal context.7 Classification and regression trees are a likely first move towards machine learning algorithms in the judicial decision-making context, due to their transparency and interpretability. Berk and Bleich (2014) offer random forests as a potential candidate ML technique for judicial contexts. Yet these more sophisticated ML methods may exacerbate the earlier-discussed reference class problem.

More data-driven machine learning methods are also less numerically stable than regression models. Re-running the algorithm with the same data but a different random initialization “seed” can give a different output. Even using different software can lead to a different result. Recent research has identified a potential culprit as the “underspecification” of complex ML models on a given training dataset (D’Amour et al., 2020). The idea is that many distinct solutions (e.g., weight configurations) may solve a classification problem equivalently, but nevertheless perform differently when deployed in real-world scenarios. In short, as different tools rely on different algorithms, legal definitions, and data collection

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7Recently the use of facial recognition technologies by municipal agencies has been banned in several US cities. https://www.theverge.com/2019/7/17/20697821/oakland-facial-recognition-ban-vote-governement-california
mechanisms, inconsistencies in predicted scores, interpretability, and predictive accuracy are likely to grow.

A second possible advance in the next generation of risk models is the move from using only curated and well-understood input measures from dedicated datasets that correlate with the outcome behavior of interest, towards using a broad range of “features” derived from fusing multiple data sources (e.g. social media), with data in multiple formats (numerical, text, image, video, network, etc.). A shift is already underway in some risk-modeling industries such as credit scoring and car insurance, where auto insurance policy rates are often determined by behavioral driving data. In China, using such behavioral big data is already common in law enforcement and tightening up the government’s social and political control. This fundamentally contrasts with the contemporary understanding of the rule of law (Chen et al., 2018), which is largely reflected in the legal systems of most Western democracies. For one, courts are concerned with the relevance of evidence as well as with ascertaining it was properly obtained (Gastwirth, 1992). For another, algorithmic consistency may not be aligned with the court’s mandate to ensure nondiscriminatory equal protection, due process, and transparency and accountability.

It is unclear whether these legal standards will continue to apply to data and algorithms used in risk assessment tools. Experience in the financial and insurance industries suggests a more pragmatic “big data” approach may ultimately prevail. Nevertheless, caution is warranted when employing predictive algorithms in the context of courts. The inconsistencies we described will only become more difficult to identify and solve. We recommend that, in addition to existing calls for transparency and accountability mechanisms (Kroll et al., 2016), only well-designed, thoroughly and regularly tested algorithmic tools are permitted in high-stakes settings (Rudin, 2019).

4 Towards a Duty of “Algorithmic Competence” for Lawyers and Judges

Some broader points follow from the above discussions. The International Bar Association (“IBA”) is the leading organization for international legal practitioners, bar associations, and law societies. The IBA has published a list of ten principles they consider universal to the legal profession worldwide, all of which, arguably, are relevant to algorithmic decision-making (the “International Principles”). The International Principles are based on “national professional rules from states throughout the world; the Basic Principles on the Role of Lawyers, . . . [and] the Universal Declaration of Human Rights.”

The International Principles reflect international attitudes towards the regulation of the legal profession. They require that lawyers provide competent representation, stating that lawyers are presumed to be “knowledgeable, skilled, and capable” when delivering legal services as part of their profession (International Principle 9). Further reinforcing this concept of competence, lawyers should provide legal services to clients “competently, diligently, promptly” (International Principle 5). Lawyers also have an obligation to protect the profession against fraudulent conduct, stating that lawyers “shall at all times maintain the highest standards of honesty, integrity and fairness towards the lawyer’s clients, the court, colleagues and all those with whom the lawyer comes into professional contact.” We argue these principles should be read as requiring lawyers to comply with their duties towards the

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8 Commentary on IBA International Principles on Conduct for the Legal Profession, intro. para. 4.
courts, clients, and opposing parties, when they utilize algorithmic tools or other digital procedures or solutions that implement a particular data mining technique.

Judges have similar ethical requirements of competence. The Bologna and Milan Global Code of Judicial Ethics “reflects and expresses fundamental values and morals” relating to “the acts of judicature and the behaviour and conduct of a judge.” The Global Code of Judicial Ethics states that the “judicial branch in general is an autonomous branch, decent and fair in its conduct, and has the ability and skills to interpret and apply the law properly.” The ability and skills to interpret and apply the law properly should include, when appropriate, the skills necessary to competently utilize decision-making tools when invited into the courtroom. Similarly, when parties (including attorneys) use algorithmic tools, to maintain the dignity, fairness, and unbiased nature of the court, these tools should only be allowed into the courtroom and legal process if the judge is sufficiently satisfied the algorithmic tool is being delivered competently, honestly, with integrity and fairness towards the court.

In the US, for example, each state adopts rules regulating legal practice for lawyers and judges. Some of those rules are mandatory, some are discretionary, and some are aspirational. The rules of professional conduct for lawyers (adopted separately for each state) require that lawyers provide competent representation, usually described as “the legal knowledge, skill, thoroughness and preparation reasonably necessary for the representation.” Lawyers also have an obligation to protect a tribunal against fraudulent conduct “that undermines the integrity” of the court’s process. Judges have similar ethical requirements of competence. The Code of Judicial Conduct for judges (adopted separately for each state) states that competence includes “the legal knowledge, skill, thoroughness, and preparation reasonably necessary to perform a judge’s responsibilities of judicial office, including the benefits and risks associated with the technology relevant to service as a judicial officer.” Similar provisions can be found in other national ethics rules.

In short, when algorithmic tools touch the legal system in any jurisdiction, lawyers have a duty to understand them. Even when using algorithmic tools, lawyers must still render independent, unbiased, and candid advice (International Principle 1), render competent advice (International Principle 2), keep client information confidential (International Principle 4), and exhibit candor to the tribunal and fairness to opposing parties and counsel (International Principle 2), among other things. Similarly, judges have the duty to understand algorithmic tools and how they affect the judge’s practice. Judges, when using or allowing the use of algorithmic tools, must maintain integrity, propriety, and equality (Global Code of Judicial Ethics 5) and make sure bias and prejudice does not manifest in the judicial process through the use of algorithmic tools (Global Code of Judicial Ethics 5.3.2), among other things.

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9 Bologna and Milan Global Code of Judicial Ethics, approved at the International Conference of Judicial independence held at the University of Bologna and at Bocconi University of Milano, June 2015
10 Model Rules of Prof’l conduct, r. 1.1
11 Model Rules of Professional Conduct, r. 3.3, cmt. 12
12 Code of Judicial Conduct, r. 2.5, cmt. 1
13 see, e.g., Solicitors Regulation Authority Code of Conduct for Solicitors, Registered foreign Lawyers (RFLs), and Registered European Lawyers (RELs). The SRA regulates solicitors and law firms of England and Wales.
The Role of Algorithmic Tools in Promoting an Honorable Judicial Process

The introduction of algorithmic tools in the judicial process should be aimed at promoting impartiality and fairness and avoiding bias and prejudice to ultimately promote an honorable judicial process. Algorithmic tools must have the goal of strengthening due processes guarantees under relevant national law, as well as universal fair trial provisions manifest in the International Covenant on Civil and Political Rights. Introducing new inconsistencies to the judicial process is contrary to this goal, and judges and lawyers (and arguably policymakers, data scientists, and legal service companies providing these algorithms) have the shared responsibility of addressing these inconsistencies, which may include eliminating (even if temporarily) the offending algorithmic tool from the judicial process. If using an algorithmic tool promotes bias or prejudice, then by extension the judge or lawyer could be engaging in such bias or prejudice contrary to his or her duties under rules of professional conduct. In short, ethical rules require judges and lawyers to be at the center of these activities as users, not passive observers.

When choosing measured outcome and predictors, judges and lawyers must participate in setting legal definitions of relevant terms, and in deciding reliable measures. Judges and other legal officers must be at the center of this process in order to guarantee the consistency of predictors. In connection with the issue of choice and quality of datasets, judges and other legal officers (including lawyers) must understand the composition and limitations of these datasets. This may include requirements of some kind of dataset disclosure form or model disclosure form to be used in court proceedings.

Judges (themselves or through expert testimony) should also be aware of differing levels of accuracy for different subgroups. For issues of communicated risk scores, judges should be adequately briefed and warned of the inherent inconsistencies of risk scores. This goes beyond instilling skepticism of the use of algorithms in sentencing because judges likely lack the required knowledge to understand algorithmic tools. Judges would also need to address issues of bounded rationality, tackle cognitive limitations, and exhibit the self-control necessary to resist personal deviations from rationality and temper any anchoring bias after seeing the results of an algorithmic tool. The question is whether this is possible for any human being.

5 Conclusion

In this article, we described four types of inconsistencies introduced by risk prediction algorithms in the judicial context. They relate to choices in measured outcome and predictors, quality of training data, predictive accuracies of subgroups, and the communication of risk scores. We shed light on the origins of these hidden inconsistencies, and proposed potential indicators and solutions.

We should mention that inconsistencies in the judicial context are neither unique to machine learning and risk prediction algorithms, nor were they introduced by them. Just as the behavior of an algorithm is influenced by the choice of training dataset, the behavior of human judges is influenced by personal life experience, socio-economic background, and prior adjudicated cases (Hogarth, 1971; Sharpe, 2018). While these analogues between algorithms and human judges exist, it is important to consider the original purpose underlying the introduction of algorithms to the judicial process: ensuring consistency and efficiency.
Consistency and efficiency are not only essential to the rule of law, but they bolster the perceived legitimacy of sentences. Yet new inconsistencies arise in the judicial process, stemming from human factors outside the scope of the legal system.

In summary, if we accept the use of algorithmic risk prediction in judicial contexts, we must be prepared to not only tolerate the inconsistency of human judges, but also new inconsistencies stemming from the designers and implementers of algorithms, data aggregation, warehousing, and processing schemes, and model selection choices by data scientists. Any resolution of these inconsistencies will only come through improved alignment of algorithmic and legal goals and objectives, and greater transparency and collaboration between data scientists, legal professionals, and policymakers.

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