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A Normative Evaluation of Algorithmic Law

TIMOTHY D ROBINSON*

Advances in technology have enabled the ability for law to be prescribed to specific circumstances according to personal attributes or fact-specific information. Law can be promulgated by a predictive algorithm which is perfectly calibrated to produce some balance of outcomes. This algorithmic law has two characteristics. It is, first, law that is highly tailored to individuals and circumstances according to a predictive model. It is, secondly, law that is dynamic and evolves over time to respond to new information. By tying law to risk or a prediction of behaviour, algorithmic law can be extremely efficient at achieving desired outcomes, which might range from reducing traffic fatalities to maximising wealth. This article presents a normative evaluation of algorithmic law through analysing two legal values that algorithmic law might undermine; the rule of law and freedom. For rule of law, it is shown that algorithmic law can undermine equality before the law and affect legal certainty. From a freedom perspective, algorithmic law can subjugate the freedom of individuals for the majority interest in new ways, and can act harshly to restrict an individual's freedom based on their past, possibly unrelated, choices. This article identifies algorithmic law as a distinct and novel category of law that has both immense potential for beneficial outcomes, and unique ability to subvert legal values in new ways.

I INTRODUCTION

For the rational study of the law the black-letter man may be the man of the present, but the man of the future is the man of statistics and the master of economics.

— Oliver Wendell Holmes, Jr.¹

Algorithmic law is law made by a predictive algorithm, “perfectly calibrated” to achieve some balance of objectives.² Such an algorithm

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1 OW Holmes “The Path of the Law” (1897) 10 Harv L Rev 457 at 469.

predicts whether a given situation is likely to produce a desired outcome and then prescribes law on the basis of this prediction. Two characteristics define algorithmic law. It is, first, law that is highly *tailored* to individuals and circumstances according to the predictive model. It is, secondly, law that is *dynamic* and will respond to new information to evolve the law over time.

To visualise this law, consider an example offered by Anthony Casey and Anthony Niblett — the regulation of traffic speed.³ Algorithmic law would prescribe an objective, such as keeping road fatalities below a certain number, then issue personalised commands to individuals according to relevant situational information. These commands, defined as *micro-directives*, could adjust permitted speed according to variables such as weather conditions, the time of day or driver history.

This article presents a preliminary normative evaluation of the desirability of algorithmic law. It does not intend to conclude whether such law is *always* desirable — the desirability of such law will depend on the particular instantiation of algorithmic law proposed. Rather, this article aims to highlight algorithmic law as a novel category of law with unique characteristics and jurisprudence, which, by its own nature, will undermine and uphold particular normative values.

Parts II and III describe different scholarship on algorithmic law and define the concept of algorithmic law. Part IV presents the argument for algorithmic law by describing the efficiency-enhancing potential of mathematically calibrated laws. Part V critiques algorithmic law according to the legal values of the *rule of law* and *freedom*.

II THE AGE OF THE ALGORITHM

Overview

We live in the “age of the algorithm”.⁴ Actuarial algorithms “that can predict individuals’ future behavior” shape important decisions in areas as widespread as education, medicine, politics, crime and insurance.⁵

Predictive algorithms can be used to assess creditworthiness.⁶ They can evaluate teachers — to the extent that some are dismissed.⁷ They can

2 Anthony J Casey and Anthony Niblett “The Death of Rules and Standards” (2017) 92 Ind LJ 1401 at 1402.

3 At 1404.

4 Cathy O’Neil *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy* (Crown, New York, 2016), back cover. O’Neil also suggests we live in the “age of data”. At 218.

5 Ariel Porat and Lior Jacob Strahilevitz “Personalizing Default Rules and Disclosure with Big Data” (2014) 112 Mich L Rev 1417 at 1434–1435; and O’Neil, above n 4, at chs 3 and 5.

6 See Ashlyn Aiko Nelson “Credit Scores, Race, and Residential Sorting” (2010) 29 JPAM 39.

7 Bill Turque “206 low-performing D.C. teachers fired” *The Washington Post* (online ed, Washington, DC, 15 July 2011). See also the 2016–2017 IMPACT programme guidebooks, for example, District of Columbia Public Schools *General Education Teachers with Individual Value-Added Student Achievement Data* (18 August 2016) at 6–8.

screen job applicants.⁸ They can predict criminal reoffending⁹ and identify patterns of crime.¹⁰ They can determine government funding for pharmaceuticals¹¹ or schools.¹² And they can identify children at a heightened risk of maltreatment.¹³

The technology that enables these predictions is artificial intelligence — more specifically, *machine learning* — which can examine “gigantic databases” of information and identify patterns that predict individuals’ future behaviour.¹⁴ As “[c]omputational power [grows] at exponential rates”¹⁵ and increasing volumes¹⁶ of data are collected from a greater number of Internet-connected sensors, these predictions will only become more accurate over time.¹⁷

Machine learning techniques allow seemingly unrelated information to be tied together in unanticipated ways. For example, it has been found that purchasing birdseed, or felt pads for furniture legs, indicates low credit risk.¹⁸ Risky driving has been correlated with risky financial decisions.¹⁹ Tesco, the retail store, has identified that customers who purchase nappies tend to have an increased demand for beer.²⁰

An organisation that can predict outcomes will have better decision making and resource allocation. For this reason, annual spending on “big data” is forecasted to reach USD 58.9 billion in 2020 (with a compound annual growth rate of 22.6 per cent).²¹ For comparison, this figure is greater than the Gross Domestic Product of Uruguay,²² and is eleven times the regular budget of the United Nations.²³

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- 8 Gideon Mann and Cathy O’Neil “Hiring Algorithms Are Not Neutral” *Harvard Business Review* (online ed, Massachusetts, 9 December 2016).
- 9 Grant T Harris and others “A Multisite Comparison of Actuarial Risk Instruments for Sex Offenders” (2003) 15 *Psychological Assessment* 413.
- 10 Michelle Dickinson “Science & Tech: Big data on crime” *The New Zealand Herald* (online ed, Auckland, 30 January 2016).
- 11 PHARMAC *Pharmaceutical Management Agency: Cost-Utility Analysis (CUA) Explained* (August 2015) <www.pharmac.govt.nz>.
- 12 Nicholas Jones “How new funding model could affect schools” *The New Zealand Herald* (online ed, New Zealand, 12 April 2017).
- 13 See “Vulnerable Children Predictive Modelling” Ministry of Social Development <www.msd.govt.nz>. See also Richard MacManus “Holding algorithms accountable” (10 July 2017) Newsroom <www.newsroom.co.nz>.
- 14 Porat and Strahilevitz, above n 5, at 1434–1435.
- 15 Casey and Niblett, above n 2, at 1410.
- 16 Andrew McAfee and Erik Brynjolfsson “Big Data: The Management Revolution” *Harvard Business Review* (online ed, Massachusetts, 1 October 2012) at 62.
- 17 Michael Chui, Markus Löffler and Roger Roberts “The Internet of Things” *McKinsey Quarterly* (online ed, New York, March 2010).
- 18 Charles Duhigg “What Does Your Credit-Card Company Know About You?” *The New York Times Magazine* (online ed, New York, 12 May 2009). See also Porat and Strahilevitz, above n 5, at 1454–1455.
- 19 Edward R Morrison and others “Health and Financial Fragility: Evidence from Car Crashes and Consumer Bankruptcy” (Coase-Sandor Institute for Law and Economics Working Paper No 655, 17 October 2013) Social Science Research Network <www.ssrn.com> at 10–12.
- 20 “Crunching the numbers” *The Economist* (online ed, London, 19 May 2012).
- 21 Ashish Nadkarni and Dan Vasset “Worldwide Big Data Technology and Services Forecast, 2016–2020” (December 2016) International Data Corporation <www.idc.com>.
- 22 The World Bank “Uruguay” <<http://data.worldbank.org>>.
- 23 “Fifth Committee Recommends \$5.4 Billion Budget for 2016–2017 Biennium as It Concludes Main Part of Seventieth Session” (23 December 2015) United Nations <www.un.org/press>.

More broadly, the technological frameworks on which algorithmic law can exist are undergoing rapid change — or are yet to be conceived. Previously-simple machines are now becoming intelligent and interconnected.²⁴ Where, formerly, algorithmic law would have needed to be stored and promulgated from a central database, blockchain technology has shown that algorithmic law could be implemented as a decentralised system.²⁵ Laws might not require human enforcement and, instead, be an inherent restriction within technology itself.²⁶ Where applications of algorithmic law might seem far-fetched or unrealistic, with the rapid pace of technological advancement it is not unfeasible to assume that such law will become viable in the near future.

Scholarship on Algorithmic Law

The growing use and importance of prediction technology has prompted a number of suggestions for how such technology might be used in law. Casey and Niblett propose regulation by *micro-directives*: context-specific legal commands that specify the exact behaviour required in a given situation. A predictive algorithm defines precise rules for individuals that are optimised to achieve a particular outcome. In this way, micro-directives are the hybrid of a rule and a standard. Each micro-directive is prospective, yet micro-directives as a whole will tend towards efficient outcomes and be “perfectly calibrated” to achieve some balance of objectives.²⁷ As well as predictive technology, micro-directives are enabled by developments in communicative technology that allow a micro-directive to be transmitted or queried in real time.²⁸

Aaron Wright and Primavera De Filippi suggest a similar idea of *algorithmic governance*: a “highly optimized” means of efficiently regulating society.²⁹ Such law might be self-enforcing; and Wright and De Filippi warn of the risk of “highly prescriptive and deterministic” law.³⁰

Ariel Porat and Lior Jacob Strahilevitz suggest that predictive algorithms should be used to determine *default rules for contracts*.³¹ Default rules which are personalised to an individual’s characteristics or past behaviour will better and more efficiently achieve outcomes than universal default rules. Such personalised default rules are the best prediction of the rules an individual would actually choose. Universal default contract rules can act against minority interests — for example, a person in a wheelchair who requires home delivery might be subject to a majority default position

24 Chui, Löffler and Roberts, above n 17.

25 Satoshi Nakamoto *Bitcoin: A Peer-to-Peer Electronic Cash System* (2008). See also “Ethereum Project” Ethereum <www.ethereum.org>.

26 Aaron Wright and Primavera De Filippi “Decentralized Blockchain Technology and the Rise of *Lex Cryptographia*” (12 March 2015) Social Science Research Network <www.ssrn.com> at 43.

27 Casey and Niblett, above n 2, at 1402.

28 At 1403–1404.

29 Wright and De Filippi, above n 26, at 41–44.

30 At 43 and 44.

31 Porat and Strahilevitz, above n 5.

that assumes pick-up from store.³² Porat and Strahilevitz suggest that default rules can be determined by machine learning techniques.³³ Through collecting data on “guinea pigs” — and using this to categorise new individuals — the default rules of similar persons can be applied.³⁴ This is an established artificial intelligence technique called *instance-based learning*.³⁵

Omri Ben-Shahar and Ariel Porat argue for a *personalised standard of negligence* — the standard of the “reasonable you”.³⁶ Information about a person is used to identify the actual risk produced by their actions (“personalized expected risk”).³⁷ A personal standard is then imposed, given what might be broadly considered as *aggravating* and *mitigating* factors affecting risk. A young person could have a standard that permits driving at a higher speed than an elderly person because the young person has a faster reaction time.³⁸ The actual risk created by each person at different speeds might be the same. It is suggested that “Big Data” can aid in the formulation of such personal standards and might use information relating to “other characteristics” that are not unique to the standard at hand — such as carelessness or a general disposition to risk.³⁹

The above examples relate to different areas of law, and each will have different critiques. However, at the same time, these ideas share a common theme — the use of precise, algorithmic predictions to tailor law to achieve better outcomes. These ideas will be broadly discussed as *algorithmic law*.

Algorithmic law might be effected without explicit enactment, on top of traditional law — explained by John O McGinnis and Steven Wasick’s concept of *legal search*.⁴⁰ A system of micro-directives can emerge through software that outperforms lawyers at providing accurate legal advice.⁴¹ This might not be *law*, but would be the best estimate of how any discretion within the law will be applied. Through a Holmes’ prediction theory perspective, McGinnis and Wasick argue that such a legal “search engine” effectively then becomes the law:⁴²

The question of “what is the case law on the discovery rule in X situation” will not be scattered among random case numbers or found in legal encyclopedias, but will instead be entirely contained within the phrase ... the search engine itself will effectively become the law.

32 At 1427.

33 At 1434–1435.

34 At 1450–1451.

35 Stuart J Russell and Peter Norvig *Artificial Intelligence: A Modern Approach* (3rd ed, Prentice Hall, Upper Saddle River (NJ), 2010) at 737–739.

36 Omri Ben-Shahar and Ariel Porat “Personalizing Negligence Law” (2016) 91 NYU L Rev 627 at 631.

37 At 633.

38 At 630.

39 At 631.

40 John O McGinnis and Steven Wasick “Law’s Algorithm” (2014) 66 Fla L Rev 991.

41 Casey and Niblett, above n 2, at 1422–1423.

42 McGinnis and Wasick “Law’s Algorithm”, above n 40, at 1023. See also 1023–1026.

Algorithmic law might also be established by private parties through the “interplay of reasonableness, industry standards, and technology”.⁴³ If legal prediction software is used by private parties to guide decision making, it might become seen as an industry standard.⁴⁴ Failure to consult, or a significant deviation from a recommended directive, might then be considered per se unreasonable in assessing standards of care.⁴⁵

III DEFINING ALGORITHMIC LAW

Algorithmic law describes laws that have two aspects in common. First, rules are highly *tailored* to individuals and circumstances — a characteristic facilitated by a predictive model. Secondly, the model for producing tailored laws is *dynamic* and will adapt as outcomes are measured against some goal. Both of these aspects are present in regular law, although to a lesser extent. It will be shown that algorithmic law is different *in degree* rather than *in kind*.

The Tailoring of Laws

The first aspect of algorithmic law is that laws are highly tailored to individuals or circumstances according to a predictive model that seeks to achieve some outcome. Laws might be prescribed to individuals within discrete categories or might vary along a continuum.⁴⁶

Tailoring is not a novel characteristic of law. Laws are already tailored. A law applying to a group, such as company directors, will not affect someone who is not a part of that group. Current laws target people who do a particular activity,⁴⁷ or are of a certain age,⁴⁸ or buy a certain product.⁴⁹ Standards of negligence can depend on the capabilities,⁵⁰ or the professional skill⁵¹ of the defendant.

The tailoring that defines algorithmic law is, therefore, a matter of degree. Where traditional law is tailored to broad categories, algorithmic law is finely calibrated and makes granular categorisations⁵² of people and situations. Such granularity is enabled by — and can only realistically be achieved with — the use of a predictive algorithm.

However, prediction alone cannot be a sufficient criterion to distinguish law as *algorithmic*. Already, legislation is enacted after considering predicted outcomes. In debating a Bill, Members of Parliament

43 Casey and Niblett, above n 2, at 1421.

44 At 1422.

45 At 1421–1422.

46 Cass R Sunstein “Deciding by Default” (2013) 162 U Pa L Rev 1 at 48.

47 See, for example, s 129A of the Sentencing Act 2002.

48 See, for example, the definition of “minor” in s 5 of the Sale and Supply of Alcohol Act 2012.

49 See, for example, s 213 of the Customs and Excise Act 1996.

50 See generally *Billy Higgs and Sons Ltd v Baddeley* [1950] NZLR 605 (CA).

51 See generally *Bolitho v City and Hackney Health Authority* [1998] AC 232 (HL); and *New Zealand Guardian Trust Co Ltd v Brooks* [1995] 1 WLR 96 (PC).

52 Sunstein uses the term *fine-grained*. See Sunstein, above n 46, at 48.

will anticipate the effects of that Bill — a process that might include economic analysis. Predictions might not be quantifiable — such as how a certain principle of law could be affected — but a prediction is still made.

The tailored aspect of algorithmic law then is no different in *kind* from any regular law. Rather, algorithmic law is different in *degree*. There becomes a point where law is so fine-grained that it takes on a new character and ought to be considered a distinct category of law.

To illustrate this, consider a basic algorithm that prescribes a speed limit given the following variables:

- (1) time of day (in hours only);
- (2) weather (good, neutral, poor);
- (3) road type (motorway, rural, semi-rural, residential, urban);
and
- (4) driver history (good, neutral, poor).

There will be 1,080 tailored situations with rules prescribed — far more than any lawmaker would traditionally attempt to define.⁵³ In form this is no different than having five tailored speed limits according to road type. However, the sheer level of tailoring that can be reached by an algorithm means the law takes on a new character.

Dynamism: Adapting the Predictive Model

The second defining aspect of algorithmic law is that it is dynamic. A prediction algorithm will gradually change and respond to new information to refine prediction accuracy. This aspect is implicit in the nature of a prediction algorithm and machine learning itself.⁵⁴

The dynamism of algorithmic law allows laws to adapt to external changes. For example, a speed limit might increase to meet a long-term improvement in car safety or reduce to respond to a sudden fluctuation in risk.⁵⁵

Algorithm-driven laws will automatically and rapidly adapt to the circumstances, optimizing according to the objective of the law. But changes to the law result in winners and losers. Frequent changes to the law may impose additional risks on individuals and may affect the willingness of individuals to invest in projects that may be subject to legal uncertainty. A smart machine will, however, be able to take into account any effects on the values of reliance investments to find a global optimum, rather than merely a local optimum.

Like tailoring, the dynamism of algorithmic law reflects the law-making that already occurs, but to a greater extent. Law change takes place by lawmakers predicting that the change will bring about a better outcome. In this regard, law is already outcome-focused. Algorithmic law might merely shift the mechanism for change from a political, discretionary assessment of outcome,

53 Calculated from the possible combinations of the given variables: $24 \times 3 \times 5 \times 3 = 1,080$.

54 See generally Russell and Norvig, above n 35, at chs 18–21.

55 Casey and Niblett, above n 2, at 1437–1438 (footnotes omitted).

to a pre-defined and precise scientific assessment. Political assessment of outcome might often be reached through scientific analysis anyway — and algorithmic law might automate choices that are already guided by economic analysis.

It is possible to avoid dynamism by using a pre-defined prediction model that is unaffected by new information. However, this accepts some level of prediction inaccuracy. Such a prediction model would produce more certain law in the short term, but would also require periodic repeal and replacement to avoid gross inaccuracy.

Overcoming Practicalities

A natural criticism of prediction-based law is to point to some practical problem in the accuracy of the prediction model, for example, faulty data or a failure to consider information.⁵⁶ For the purposes of presenting a conceptual normative evaluation, I will overlook these concerns and assume the algorithm is highly accurate. I also avoid criticisms that the wrong, or overly narrow, goal would be prescribed to a prediction algorithm.⁵⁷ This is best left as the domain of the lawmaker. Finally, I avoid the idea that individuals might *game the system* and change their behaviour to trick the prediction model. I assume that implicit in accurate predictions is the need to account for this possibility and create a model that cannot be tricked by minor changes in behaviour.⁵⁸ Of course, incentivising an individual to change their behaviour to be more desirable — for example, by taking fewer risks — is the entire purpose of such algorithmic law.

IV THE ARGUMENT FOR ALGORITHMIC LAW

The Death of Rules and Standards

The promise of algorithmic law is that by tailoring law to specific groups or situations — and updating tailored law with new information over time — the law can better achieve some functional goal. This goal might be anything. Maximising wealth is a natural goal for algorithmic law, but so too might be other objectives decided by the lawmaker, such as reducing traffic

56 See Anna Chalton “Rape Myths and Invisible Crime: The Use of Actuarial Tools to Predict Sexual Recidivism” (2015) 2 PILJNZ 19 at 45–48.

57 See O’Neil, above n 4, at 50–59. O’Neil describes the problem of narrow goals by using the example of the college ranking system developed by US News & World Report in the United States. O’Neil argues the rankings use *proxies* to assess college quality that cannot fully capture educational experience. Rankings might be useful at identifying a top-tier college from a mid-tier college, but cannot helpfully distinguish between two mid-tier colleges. If these rankings guide students’ college selections, a self-fulfilling prophecy is created in that top students seek to attend a top-ranked college, which further increases that college’s ranking. In consequence, colleges will focus their efforts on the particular criteria assessed, even if those criteria do not capture the full picture of college quality.

58 Casey and Niblett, above n 2, at 1423.

fatalities. How this functionalism is achieved is best understood from a law and economics analysis of rules and standards.

Algorithmic law is a “hybrid” of rules and standards, meaning that functional goals can be better achieved while minimising other costs.⁵⁹ The “canonical”⁶⁰ law and economics approach to rules and standards is given by Louis Kaplow.⁶¹ Rules are precise and *ex ante* in nature, while standards leave open ambiguity that is clarified retrospectively after an individual acts in an unprecedented manner.⁶² An example of a rule is the “bright-line test” that deems profit from disposing land within two years as taxable income.⁶³ This rule overrides the general standard that capital gain from a property is only taxable if the property was acquired for the purpose or intention of disposal.⁶⁴ The distinction between rule and standard is one of degree.⁶⁵ A law prohibiting “vulgar behaviour” might be considered to be a rule or a standard depending on whether the set of acts that are “vulgar” are predominantly defined *ex ante* or *ex post*.⁶⁶ Rules are typically expensive to create because all possible acts and areas of application need to be considered. However, because rules are certain, their enforcement is inexpensive.⁶⁷ Standards are cheap to create and can be applied flexibly to adhere to a goal, but because of this will be expensive to enforce. Individuals subjected to a standard will also incur costs in learning — and seeking advice on — the scope of a standard.

Whether a rule or a standard is desirable for lawmakers will depend on the particular error, decision and uncertainty costs.⁶⁸ Lawmakers effectively “trade-off between certainty and calibration”.⁶⁹ A standard will be most calibrated to achieve a functional goal, but will lack certainty and incur ongoing enforcement costs. This is why standards are typically preferred only when behaviour is diverse and infrequent.⁷⁰ Rules are certain, but their lack of calibration means they will be over-inclusive and apply even when the underlying legal justification does not — for example a traffic light will continue to order cars to stop even when there is no other traffic on the road.⁷¹

Algorithmic law changes this dichotomy in a way that Casey and Niblett describe as the death of rules and standards:⁷²

59 Casey and Niblett, above n 2, at 1410.

60 McGinnis and Wasick, above n 40, at 1029.

61 Louis Kaplow “Rules Versus Standards: An Economic Analysis” (1992) 42 *Duke LJ* 557 as cited in McGinnis and Wasick, above n 40, at 1029.

62 Casey and Niblett, above n 2, at 1407.

63 Income Tax Act 2007, s CB 6A.

64 Section CB 6A(6). See also s CB 6.

65 Kaplow, above n 61, at 600–601.

66 At 600–601.

67 At 563.

68 Casey and Niblett, above n 2, at 1407–1408.

69 At 1402.

70 At 1408.

71 See Kimberly Kessler Ferzan “Prevention, Wrongdoing, and the Harm Principle’s Breaking Point” (2013) 10 *Ohio St J Crim L* 685 at 688.

72 Casey and Niblett, above n 2, at 1410.

... the result will be a new hybrid form of law that is both rule and standard. The lawmaker can set a broad objective, which might look like a standard. But the predictive technology will take the standard and engineer a vast catalog of context-specific rules for every scenario.

To illustrate that this hybrid can be preferable to a rule or standard, Casey and Niblett imagine an algorithm that predicts whether a patient requires surgery. Two scenarios are given, with algorithms of different accuracies:⁷³

Under scenario 1 [a bad prediction algorithm], the technology should have no effect on your decision as a regulator to implement a rule or a standard. You should implement a standard and determine liability on a case-by-case basis, learning more about doctors' behavior over time.

Under scenario 2 [an accurate prediction algorithm], however, the optimal form of the law will be different. The machine's predictions provide the exact content of the law. The machine provides microdirectives for each and every scenario. The over- and underinclusivity associated with simple rules have disappeared. ... The justification for relying on *ex post* adjudication of standards — reducing the error costs of rules — is gone. Further, we have an added benefit of eliminating uncertainty for the doctors. If they follow the directive of the machine, they know they will not be held liable.

The desirability of a system of micro-directives does not depend on a perfect prediction algorithm.⁷⁴ Rather, there reaches what Casey and Niblett describe as:⁷⁵

... a point where the technology is *good enough* that the costs of using a microdirective are sufficiently low so that there is no longer any need to use traditional rules or standards

Highly calibrated law — akin to that of a standard — then becomes possible in areas where it would have previously been inefficient.

Calibrated Law: Eliminating Risk Subsidisation

To illustrate the benefits of calibration, consider how calibrated law can make individuals liable for their own risk. Porat and Strahilevitz discuss this in the context of personalised default rules for contracts.⁷⁶ Some laws that apply generally cause “cross subsidies” between groups in society.⁷⁷ One group will face higher costs, or greater restrictions on liberty, because of the behaviour of another group. Speed limits are an example of this: it might be

73 At 1414–1415.

74 At 1415.

75 At 1415 (emphasis in original).

76 Porat and Strahilevitz, above n 5, at 1453–1454.

77 At 1453–1454.

safe for some people to drive at a high speed, but the general prescribed limit must be lower than this to account for drivers who are unskilled or easily distracted.

Algorithmic law reduces this cross subsidisation. Consider the Consumer Guarantees Act 1993, which mandates a guarantee for the quality of products bought in trade.⁷⁸ Businesses pass the costs of this to consumers uniformly, but, naturally, some consumers will be more reckless in how they treat their product and will have a higher probability of claiming their guarantee. This means that other, more cautious, consumers effectively subsidise the behaviour of the group of risk-taking consumers prone to using their guarantee. In contrast, algorithmic law can be calibrated so that costs are borne more proportionally. There might be a less stringent guarantee for risky consumers — meaning that cautious consumers can benefit from the same guarantee at a reduced cost.⁷⁹

A more complex example can be found in New Zealand's 90 day trial law for new employees.⁸⁰ Employers, facing the risk that a potential employee is not as they appear in an interview, can contract with the employee to undergo a 90 day trial. During a trial, the employee can be dismissed at any time and cannot bring legal proceedings in respect of that dismissal.⁸¹ This trial period has become common practice, with 66 per cent of hiring employers employing one or more of their new staff on a trial.⁸² The trial benefits “people at the margins of the labour market” who appear to be risky employees (but would remain employed at the end of a trial) as well as the employers who would like to give such people a chance.⁸³ However, the trial also creates a general risk for non-risky new employees, who, during the trial, might be dismissed with reduced rights and in a way that would otherwise be illegal — for example, they could be immediately dismissed following an economic downturn.

Algorithmic law can limit this general risk to only the people “at the margins” who the law purports to help. It might dictate that a trial period only be available for the set of employees who, according to a predictive algorithm, appear risky (for example, those who are youthful or have a transient employment history). These employees can then retain the benefit of the trial, while regular employees, who would be employed regardless of the trial, are not subjected to the risk of sudden dismissal. This is law that could otherwise be implemented as a standard but would likely be prohibitively uncertain.

The following table sets this idea out in more detail:

78 Consumer Guarantees Act 1993, ss 6–7.

79 In this example, all consumers would then pay less for a product, but risk-averse consumers would benefit by retaining the same guarantee. It is feasible that a company could implement its own personalisation by tailoring price to the risk for each guarantee.

80 Employment Relations Act 2000, s 67A.

81 Employment Relations Act 2000, s 67A(2)(c).

82 Ministry of Business, Innovation & Employment *National Survey of Employers 2014/15: Summary Findings* (April 2016) at 4.1.1. The number increased from 63 per cent in 2013/2014 and 59 per cent in 2012/2013. It was not recorded in 2015/2016.

83 See comments made by Hon Kate Wilkinson MP. (9 December 2008) 651 NZPD 318 and 319.

Employee	Employed without 90 day trial law?	Employed with 90 day trial law? (with additional risk of dismissal within 90 days)	Employed with an algorithmic law trial period?
Appears risky, is a bad employee	No	Yes (then dismissed within the trial period).	Yes (then dismissed within the trial period).
Appears risky, is a good employee	No	Yes (additional risk of dismissal within 90 days).	Yes (additional risk of dismissal within 90 days).
Appears non-risky, but is a bad employee	Yes (then dismissed under normal laws).	Yes (then dismissed within the trial period).	Yes (then dismissed under normal laws).
Appears non-risky, and is a good employee	Yes	Yes (additional risk of dismissal within 90 days).	Yes; no additional risk of other dismissal.

Calibrated Law: Personalisation

Much of the appeal of algorithmic law relates to its potential for personalisation. While it is possible for algorithmic law to be unrelated to personal attributes (for example, a speed limit that varies with weather), it is through personalising law that the greatest reduction in risk subsidisation is likely to occur.

The efficiency of personalised standards for negligence is examined by Ben-Shahar and Porat.⁸⁴ They analyse two types of personalisation — skill-based and risk-based — and, broadly, conclude that both types of personalisation are efficient and optimise levels of care.

Skill-based personalisation reflects the different costs that individuals incur to reach different standards of care. Ben-Shahar and Porat identify that “[m]ore skilled injurers can achieve the same reduction in risk as unskilled injurers by spending less on care.”⁸⁵ The efficiency of this is “wholly intuitive”.⁸⁶

It pays to impose higher burdens on the more competent actors to take advantage of their greater productivity. Thus, the driver who is more competent in operating sophisticated technical equipment should probably use it, while the less competent driver perhaps should not. ...

Personalized standards, although imposing more differentiated *levels* of care, impose less differentiated *costs* of care on the various types of injurers.

84 Ben-Shahar and Porat, above n 36.

85 At 647.

86 At 649 (emphasis in original).

Risk-based personalisation reflects the variations in risk of harm that are created by people operating at the same standard of care. Two people exercising the same level of care will not necessarily produce the same outcome due to differing knowledge and experience.⁸⁷ Risk-based personalisation is also efficient.⁸⁸

It pays to impose higher burdens on the more risky actors since any additional burden would produce more risk reduction for the high-risk actor than for the low-risk actor. Thus, the high-risk driver with the poor instincts should take more care than the driver with the sharper instincts. Similarly, the high-risk doctor with less experience and knowledge should take more care than the more experienced and knowledgeable doctor.

It appears to contradict that it is efficient for both unskilled individuals to take less care and riskier individuals to take more care; however this is reconciled in two ways.⁸⁹ Care and precaution can be viewed as having “multiple dimensions”:⁹⁰

A doctor should take a low level of the type of precautions that she is unskillful in deploying. That, in turn, makes her relatively riskier and justifies imposing upon her a higher level of care with respect to other precautions.

The alternative reconciliation is to view skill and risk as “pulling in a different direction”.⁹¹ The net combination of the forces then dominates.⁹²

If, for example, only one type of precaution is available, a driver who is both riskier and low skill may in the end be required to take either a higher or lower level of care, depending on which effect dominates. It is therefore possible that despite the low skill in applying this single-dimensional precaution, the high-risk driver may be required after all to take a higher level of care.

Prediction of Choice

Algorithmic law can be used to substitute the choices of individuals. This is suggested by Porat and Strahilevitz for default contract rules.⁹³ Consider New Zealand laws requiring informed consent for medical procedure. In situations where informed consent is not possible — for example, the patient is unconscious and there are no persons with the power to consent for the patient — a doctor may decide to carry out the procedure. This is permitted if the doctor, having ascertained the views of the patient, believes “on reasonable grounds, that the provision of the services is consistent with the

87 At 650.

88 At 651–652.

89 At 652.

90 At 652.

91 At 652.

92 At 652.

93 See Porat and Strahilevitz, above n 5, at 1442–1444.

informed choice the [patient] would make if [they] were competent”.⁹⁴ Algorithmic law could provide an alternative to this approach and issue a directive to the doctor, predicting consent from known information (such as prior consent given by the patient). This might be a more accurate prediction mechanism than the doctor’s own views and may align better with the desired role and liabilities of doctors.

V CRITIQUES OF ALGORITHMIC LAW

This part offers two critiques of algorithmic law. The first critique is that algorithmic law undermines aspects of the rule of law, specifically: equality before the law; and certainty of law. The second critique is that algorithmic law can constrain individual rights to freedom.

Rule of Law

1 Equality Before the Law

Equality has long been a fundamental value of the rule of law. AV Dicey’s famous conception of the rule of law prescribed the “equal subjection of all classes” to the law of the land.⁹⁵ Lord Bingham has described equality before the law as a “cornerstone” of society,⁹⁶ while John Locke wrote against law varied “in particular cases” and promoted “one rule for rich and poor, for the favourite at Court, and the country man at plough”.⁹⁷ Rule of law was a value called upon by Lord Scarman in 1983 to reject the argument that habeas corpus protection did not apply to non-British nationals:⁹⁸

Every person within the jurisdiction enjoys the equal protection of our laws ... He who is subject to English law is entitled to its protection. This principle has been in the law at least since Lord Mansfield freed “the black” in *Sommersett’s Case* (1772) 20 St.Tr. 1.

Equality in law reflects the idea that equal treatment is just; a universal value described by Justice Scalia as a “motivating force of the human spirit”.⁹⁹

Parents know that children will accept quite readily all sorts of arbitrary substantive dispositions ... But try to let one brother or sister watch television when the others do not, and you will feel the fury of the fundamental sense of justice unleashed.

94 Code of Health and Disability Services Consumers’ Rights, Right 7(4)(c)(i).

95 AV Dicey *Introduction to the Study of the Law of the Constitution* (10th ed, Macmillan, London, 1959) at 202.

96 Tom Bingham *The Rule of Law* (Penguin Books, London, 2011) at 55.

97 Peter Laslett (ed) *John Locke: Two Treatises of Government* (2nd ed, Cambridge University Press, London, 1967) at [142].

98 *R v Secretary of State for the Home Department, ex parte Khawaja* [1984] 1 AC 74 (HL) at 111.

99 Antonin Scalia “The Rule of Law as a Law of Rules” (1989) 56 U Chi L Rev 1175 at 1178.

Equality also serves a constitutional purpose: manifesting in concepts of legislative generality and bills of attainder which recognise that unequal and specific law can undermine the judiciary.¹⁰⁰ As Justice Jackson of the Supreme Court of the United States described in 1949:¹⁰¹

... equality is not merely abstract justice ... there is no more effective practical guaranty against arbitrary and unreasonable government than to require that the principles of law which officials would impose upon a minority must be imposed generally.

However, the nature of law makes equality before the law difficult to define. Laws apply conditionally: all members of society are subject to a law, yet only some might trigger the conditions that impose substantive outcomes.

Consider New Zealand's Health and Safety Act, which imposes health and safety duties on workers, officers and "person[s] conducting a business or undertaking".¹⁰² In *form* this law applies to all people, but in *substance* only a person meeting the definition of a relevant category could ever be burdened with its effect. This is the same for other laws, including those commonly held up as an aberration to equality before the law: laws that apply only to citizens of a particular country,¹⁰³ laws excluding women from the military draft,¹⁰⁴ laws that are applied randomly at the toss of a coin.¹⁰⁵ There must, therefore, be *some* substantive measure for determining acceptable and unacceptable inequality before the law. This is not straightforward, as different views exist on the limitations of legal equality. As Bingham observes, the principle of equality before the law has, in liberal countries, not deterred the enactment of anti-terrorism laws that target groups by nationality.¹⁰⁶

A starting point is the scholarship of Bruno Leoni, who in *Freedom and the Law* argued that *any* legal categorisation undermines equality of law. Drawing on Dicey's denouncement of separate administrative tribunals, he wrote:¹⁰⁷

Within each category people will all be "equal" before the particular law that applies to them, regardless of the fact that other people, grouped in other categories, will be treated quite differently by other laws. ... Thus, by a slight change in the meaning of the principle of "equality," we can pretend to have preserved it. Instead of "equality before the law," all that we shall have will then be *equality before each of the two systems of law*

100 Duane L Ostler "Legislative Judging: Bills Of Attainder in New Zealand, Australia, Canada and the United States" (2014) 22 Wai L Rev 78 at 78.

101 *Railway Express Agency v People of State of New York* 336 US 106 (1949) at 466–467.

102 Health and Safety at Work Act 2015, ss 17–19.

103 See generally commentary on Japanese internment camps in World War Two, for example, Diane P Wood "The Rule of Law in Times of Stress" (2003) 70 U Chi L Rev 455 at 462.

104 *Rostker, Director of Selective Service v Goldberg* 453 US 57 (1981).

105 See Ronald Dworkin *Law's Empire* (Belknap Press, Cambridge (Massachusetts), 1986) at 178–184.

106 Bingham, above n 96, at 58.

107 Bruno Leoni *Freedom and the Law* (3rd ed, D van Nostrand, Princeton (NJ), 1961) at 68–69 (emphasis in original).

enacted in the same country, or, if we want to use the language of the Dicean formula, we shall have *two laws of the land instead of one*. Of course, we can, in the same way, have three or four or thousands of laws of the land—one for landlords, one for tenants, one for employers, one for employees, etc. This is exactly what is happening today in many Western countries where lip service is still paid to the principle of “the rule of law” and hence of “equality before the law.”

Such a strict view of equality cannot be said to prevail in modern theory. For Leoni, progressive taxation was incompatible with the ideals of equality in law, yet such taxation continues to be a core feature of a liberal state over fifty years later.¹⁰⁸ That specific rules continue to exist for employers and landlords shows that there must be some modern compromise on the ideal of equality before the law. For most scholars, this compromise depends on the extent to which inequality in law is justified; a view described by Richard Posner as the law having a “rational structure”.¹⁰⁹

There must be a “convincing distinction” between two categories in law for there to be acceptable inequality.¹¹⁰ Bingham argues this distinction is met if a categorisation is “unobjectionable” and “relevant” to the distinction made between groups.¹¹¹ Therefore, non-nationals may be subject to deportation because citizenship is a defining feature of their group, but they cannot be excluded from the protection of habeas corpus because that would be arbitrary.

Yet any inequality prescribed by an algorithm will be *relevant* or justified along statistically *convincing* lines. This is the argument for economic justice presented by Posner:¹¹²

Economic theory is a system of deductive logic: when correctly applied, it yields results that are consistent with one another. Insofar as the law has an implicit economic structure, it must be rational; it must treat like cases alike.

That there is some mathematical explanation for differential treatment does not mean such treatment is unobjectionable. If non-nationals have a higher risk of terrorism than nationals, must this be accepted as a statistical feature of their group that justifies alternative law? It is Bingham’s second idea of “objectionable” differentiation that is relevant for algorithmic law.

(a) Objectionable Categorisations

Laws prohibiting discrimination have long provided for certain rights of equal treatment to mitigate wrongful biases in society. In New Zealand,

108 At 70. The work was originally published in 1961.

109 Richard A Posner *The Economics of Justice* (Harvard University Press, Cambridge (Massachusetts), 1981) at 75.

110 George P Fletcher “Equality and the Rule of Law” (1990) 10 Tel Aviv U Stud L 71 at 80–81.

111 Bingham, above n 96, at 57.

112 Posner, above n 109, at 75.

prohibited grounds of discrimination are listed in s 21 of the Human Rights Act 1993 and include sex, race, ethical belief, age, political orientation and sexual orientation.

As stated in *Brown v Board of Education of Topeka*, even differential treatment of a group in name only can be detrimental.¹¹³

Segregation ... has a detrimental effect upon the colored children. The impact is greater when it has the sanction of the law; for the policy of separating the races is usually interpreted as denoting the inferiority of the negro group.

Discrimination is a complex area of law and ethics, and differential treatment will not always be discriminatory:¹¹⁴

On the one hand we think disabled people should be treated the same as other people. They should be able to compete fairly on merit for prized positions in society, in employment and in public life. On the other hand we think some accommodation should be made for their disabilities.

This article does not intend to delve into the limitations of discrimination law. It is sufficient to observe that there are categories of established discrimination where differential treatment is presumptively undesirable.

Algorithmic law might be presented as a solution to differential treatment — a fair and mathematical test that eliminates human discretion and unconscious bias.¹¹⁵ Yet, as observed by Cathy O’Neil, bias might merely be “camouflaged” by technology.¹¹⁶ Embedded within algorithmic models are “a host of assumptions, some of them prejudicial”.¹¹⁷ Predictive algorithms are constructed, “not just from data but from the choices we make about which data to pay attention to”, and involve assumptions that are “fundamentally moral”.¹¹⁸

The idea that algorithmic law cannot be discriminatory if it is *blind* to prohibited grounds of discrimination lacks truth for two reasons. First, as a practical feature of prediction algorithms, discrimination can occur by inference of a prohibited ground, even if this is not an explicit variable. Race can be predicted from its correlation with other information, such as postcode or online behaviour.¹¹⁹

Secondly, as critics of neutrality have argued, even neutral law can produce coercive or discriminatory results because of underlying societal

113 *Brown v Board of Education of Topeka* 347 US 483 (1954) at 494.

114 Nicholas Mark Smith “Basic Equality and its Applications” (PhD Thesis (Law), University of Auckland, 2006) at 73.

115 Casey and Niblett, above n 2, at 1428.

116 O’Neil, above n 4, at 25.

117 At 25.

118 At 218.

119 Alistair Croll “Big data is our generation’s civil rights issue, and we don’t know it” (2 August 2012) O’Reilly Radar <<http://radar.oreilly.com>> as cited in Porat and Strahilevitz, above n 5, at 1435.

inequalities. Mary Joe Frug gives an example of the inequalities caused by neutral prostitution law because “most sex workers are women”:¹²⁰

...even though anti-prostitution rules could, in theory, generate parallel meanings for male and female bodies, in practice they just don't. ... By characterizing certain sexual practices as illegal, these rules sexualize the female body. They invite a sexual interrogation of every female body: Is it for or against prostitution?

The above two points are reflected in criticisms of the Northpointe crime prediction software used in Florida to assess criminal risk.¹²¹ The software was found to falsely identify black people as future offenders almost twice as frequently as it falsely identified white people. While the software does not have any data on race, it takes information on family members who have been imprisoned, acquaintances who have been arrested or have convictions for illegal drugs, and a person's socioeconomic status.¹²² In this way the software, and algorithmic law more generally, might codify police and judicial bias, and reinforce pre-existing social inequalities. These concerns were expressed in 2014 by then Attorney General of the United States, Eric Holder:¹²³

Here in Pennsylvania and elsewhere, legislators have introduced the concept of “risk assessments” that seek to assign a probability to an individual's likelihood of committing future crimes and, based on those risk assessments, make sentencing determinations. Although these measures were crafted with the best of intentions, I am concerned that they may inadvertently undermine our efforts to ensure individualized and equal justice. By basing sentencing decisions on static factors and immutable characteristics — like the defendant's education level, socioeconomic background, or neighborhood — they may exacerbate unwarranted and unjust disparities that are already far too common in our criminal justice system and in our society.

(b) Seemingly Random Categorisations

Aside from discriminatory categories, it is possible that other, seemingly random, categorisations are objectionable. A law might be different for attractive and unattractive people. Cricket players, if seen as prone to some crime, might be prescribed harsher sentences than rugby players. Ronald Dworkin describes laws enforced along arbitrary grounds as “checkerboard” laws.¹²⁴

120 Mary Joe Frug *Postmodern Legal Feminism* (Routledge, New York, 1992) at 131–132.

121 Julia Angwin and others “Machine Bias” *ProPublica* (online ed, New York, 23 May 2016). See also their analysis: Julia Angwin and others “How We Analyzed the COMPAS Recidivism Algorithm” *ProPublica* (online ed, New York, 23 May 2016).

122 “Sample-COMPAS-Risk-Assessment” *ProPublica* <www.propublica.org>.

123 Eric Holder, Attorney-General of the United States (speech at the National Association of Criminal Defense Lawyers 57th Annual Meeting and 13th State Criminal Justice Network Conference, Philadelphia, 1 August 2014).

124 Dworkin, above n 105, at 179 (footnotes omitted).

Most of us, I think, would be dismayed by “checkerboard” laws that treat similar accidents or occasions of racial discrimination or abortion differently on arbitrary grounds. Of course we do accept arbitrary distinctions about some matters: zoning, for example. ... But we reject a division between parties of opinion when matters of principle are at stake.

For Dworkin, checkerboard laws are repugnant because they offend the political virtue of *integrity*, a value that stands alongside fairness and justice.¹²⁵ Integrity commands consistency in the principles underlying the law. Arbitrary law lacks integrity “because it must endorse principles to justify part of what it has done that it must reject to justify the rest”.¹²⁶ Through integrity, equality before the law is substantively protected by commanding consistency in values.¹²⁷

We insist on integrity because we believe that internal compromises would deny what is often called “equality before the law” and sometimes “formal equality.” ... The equal protection cases show how important formal equality becomes when it is understood to require integrity as well as bare logical consistency, when it demands fidelity not just to rules but to the theories of fairness and justice that these rules presuppose by way of justification.

Algorithmic law might lack integrity because of inconsistency in principle. Tailoring laws allows for values to be qualified and applied differently to different individuals. The laws provided for some are also laws rejected for others.

However, such inconsistency might also be justified as having integrity. Dworkin describes checkerboard laws as “internal compromises” of principle that exist arbitrarily or to resolve political division.¹²⁸ It might be reasoned for algorithmic law that seemingly checkerboard laws exist *because* of integrity in principle. Consider a law that issues the death penalty only to educated and wealthy persons. This might be seen as inconsistent in the sense that the death penalty is both endorsed as a criminal sanction and rejected as immoral. But if the motivating principle is deterrence of crime at all costs, a death penalty might be consistent! On this view, if the death penalty was restricted to cases where deterrence was expected to be successful (perhaps educated, wealthy persons), this would be consistent with legal integrity.

In this way, the legitimacy of unequal categorisation returns to the territory of *justification*. Checkerboard laws are a useful analogy of undesirable law. However, the definition of such law hinges on arbitrariness, and so whether algorithmic law can be said to be checkerboard (and offend legal integrity) will depend on the force of justification for such a categorisation in law.

125 At 183–184.

126 At 184.

127 At 185.

128 At 178–179.

(c) Equality Conclusion: Trade-off with Accuracy

Algorithmic law must balance the accuracy of its predictions with equality before the law. Porat and Strahilevitz argue that, in the context of default rules, accuracy is more important:¹²⁹

... because gender and race can be reliable predictors of current preferences and future behavior, entirely excluding these variables from an algorithm leaves a great deal of predictive power on the table. Most people would probably prefer an algorithm that knows their race and gender and, as a result, more accurately predicts their preferences...

This argument is likely to be unpersuasive beyond opt-out default rules. For law with more significant consequences, some accuracy will need to be sacrificed to prevent categorisations that are discriminatory or objectionable.¹³⁰

It is difficult to find a clear explanation of permissible inequality in law that holds when applied to algorithmic law. Concepts such as *justification* and *objectionable* quickly fall away or become circular when applied beyond the situations we instinctively *feel* are acceptable or repugnant.

However, implicit in these criteria seems to be the broader idea that people should not be unfairly judged on something they cannot change. This is the product of two variables: the degree of impact a law has on a person; and how easy it is for that person to move between the groups the law distinguishes. As technology allows tailored groups to be more precisely defined, there is an increasing need for the law to catch up and develop clearer principles of what exactly is required by equality before the law.

2 Certainty of Law

Legal certainty is the second aspect of the rule of law that could be undermined by algorithmic law.

(a) Rationale for Certainty

The rationale for certainty in private law is best described by Friedrich Hayek's argument for rules of just conduct. According to Hayek, rules ought to be independent of ends but provide certainty of means — protecting the “recognizable private domains” of individuals and enabling spontaneous order.¹³¹ Certain law facilitates transactions by providing information for decision-making and clarifying “the particular things [individuals] can count

129 Porat and Strahilevitz, above n 5, at 1467 (footnotes omitted).

130 O'Neil, above n 4, at 210.

131 FA Hayek "The Principles of a Liberal Social Order" (1966) 31 IL Politico 601 at 603.

on being able to use” in the market.¹³² For individuals to be free and rational actors, they need to be able to make long-term decisions — a prerequisite of which is certain law.

More broadly, certainty of law also protects against arbitrary discretion and abuse of public power. In criminal law, this is reflected in the expectation that offences are prospective and citizens are provided with “fair warning”.¹³³ Non-publication or unavailability of a statutory instrument may be a defence to a crime that is committed unknowingly.¹³⁴

It was the importance of legal certainty that led Jeremy Bentham to call for widespread codification of law.¹³⁵

The grand utility of the law is certainty: unwritten law does not—it cannot—possess this quality; the citizen can find no part of it, cannot take it for his guide; he is reduced to consultations—he assembles the lawyers—he collects as many opinions as his fortune will permit; and all this ruinous procedure often serves only to create new doubts

However, despite algorithmic law being heavily codified, uncertainty might arise from the plurality of tailored laws, changes in law over time and issues relating to the accessibility of law.

(b) Uncertainty Due to the Plurality of Tailored Laws

Porat and Strahilevitz discuss uncertainty in the context of personalised default contract rules, where they focus on the uncertainty resulting from the *number* of tailored default rules.

A system of tailored laws, calibrated “too finely along a continuous range”, might increase uncertainty.¹³⁶ An individual will need to invest effort to learn the particular laws that apply to them. While a system of uniformly applied law also requires an individual to learn the relevant rules, these learning costs are generally reduced if the rules also apply to everyone else.¹³⁷

However, tailoring might make it easier for individuals to anticipate the law and *increase* certainty. In the context of default contract rules, Porat and Strahilevitz observe that an individual “*already knows* a great deal about [their] preferences and characteristics, which are the factors driving the choice among multiple personalized default rules”.¹³⁸ The same point is made by Ben-Shahar and Porat in regard to personalised negligence law:¹³⁹

132 FA Hayek *Law, Legislation and Liberty: The Mirage of Social Justice* (University of Chicago Press, Chicago, 1976) vol 2 at 123.

133 AP Simester and WJ Brookbanks *Principles of Criminal Law* (4th ed, Brookers, Wellington, 2012) at 28–29.

134 At 28–29.

135 Jeremy Bentham *The Works of Jeremy Bentham* (William Tait, Edinburgh, 1843) vol 3 at 206.

136 Ben-Shahar and Porat, above n 36, at 675.

137 Porat and Strahilevitz, above n 5, at 1458.

138 At 1458 (emphasis in original).

139 Ben-Shahar and Porat, above n 36, at 675.

...it often would be easier for injurers to anticipate personalized standards than uniform ones, because they know more about their own characteristics than about the general distribution of characteristics in society.

Someone who knows they are prone to risk-taking will also know that they are likely subject to more restrictive laws and can assume they need to take greater precautions to stay within the law. Technology further enables the certainty of tailored law. For instance, micro-directives that communicate legal commands to an individual in real time leave no doubt about the required course of action for complying with the law.

Finally, the success of algorithmic law requires certain, accessible law. If it is too expensive for an individual to determine the law, they will instead accept liability equal to the average harm. Kaplow makes this argument in regard to standards that are too complex. If it is too expensive for an individual to determine their liability, they will instead pay the average of the harm caused rather than try to follow the standard — and the law will not achieve any change in behaviour:¹⁴⁰

In this instance, their behavior will be the same under both formulations of the law. At the enforcement stage, applying the complex standard will be more costly. But this will be a waste, because behavior will not be improved by avoiding over and underinclusiveness. As a result, the simple rule would be superior. Achieving a better fit between the law and behavior is accomplished only if individuals are induced to conform their behaviour to the legal norm.

For these reasons it is likely that the uncertainty caused by the plurality of tailored laws is minimal, and would be offset by the promulgation potential for algorithmic law.

(c) Uncertainty Due to Dynamism

The dynamic aspect of algorithmic law also has the potential to increase uncertainty in law. Inherent in the prediction models that prescribe law is a need for ongoing refinement. This means that law might vary from one day to another and gradually update to better align with the desired goal.

Bruno Leoni describes how variations in law over time produce uncertainty. Legislation produces “short-run” certainty of the law, but in the long-term the ability to repeal legislation causes some base level of uncertainty in law:¹⁴¹

The certainty of the law, in the sense of a written formula, refers to a state of affairs inevitably conditioned by the possibility that the present law may be replaced at any moment by a subsequent law. The more intense and accelerated is the process of law-making, the more uncertain will it be that present legislation will last for any length of time.

¹⁴⁰ Kaplow, above n 61, at 592.

¹⁴¹ Leoni, above n 107, at 80.

This uncertainty also exists with algorithmic law, which, like normal law, can be repealed. However, algorithmic law has additional uncertainty in that its application might vary from day to day. While a predictive algorithm must be codified, the future data that it will use to refine its predictions cannot be known in advance. Therefore, an individual cannot know for certain which tailored category they will fall into and what the applicable law will be. Individuals must predict the results of the legal algorithm by guessing future data.

The uncertainty of algorithmic law is less pronounced than it first seems. An established prediction model is unlikely to be heavily influenced by new data, given the amount of previous data that has already been incorporated into the model. Change is likely to be gradual and infrequent, responding to changing behaviours over time. However, for long-term planning, even gradual change is significant. In addition, there is always a risk that some external, behaviour-changing event will sharply redefine the law.

Uncertainty is most pronounced when dynamism is combined with tailored categories along lines of past choices. An individual, making a choice, cannot know for certain the category in which their choice will place them in the future, particularly when the weighting given to past choices is indeterminate.

(d) Accessibility of Algorithmic Law

Even if algorithmic law is precisely codified and does not change over time, there is still a concern that such law might lack cogency. Bingham discusses certainty of law within the larger idea of accessibility of law.¹⁴² Legal certainty fits within a broader need for the governed to *understand* the law in order for it to have effect. This idea is reflected in comments made by Lord Mansfield in 1761:¹⁴³

The daily [negotiations] and property of merchants ought not to depend upon subtleties and niceties; but upon rules, easily learned and easily retained, because they are the dictates of common sense, drawn from the truth of the case.

Algorithmic law might both enhance and suppress different aspects of law's accessibility. On one hand, predictive algorithms are complicated and their workings are beyond the understanding of most people (including lawyers!). It might be difficult to discern the principles of the law or anticipate how a predictive algorithm will operate in the future.

However, the ability of algorithmic law to be queried and respond with a simple and clear directive holds merit. Laws are *already* complex and beyond many people's understanding. Bingham describes a 2008 United

142 Bingham, above n 96, at ch 3.

143 *Hamilton v Mendes* (1761) 2 Burr 1198 at 1214, 97 ER 787 at 795 as cited in Bingham, above n 96, at 38.

Kingdom Court of Appeal case in which, on the eve of judgment, the parties and judges discovered subsequently-enacted regulations which rendered the debated regulations no longer relevant.¹⁴⁴ While noting the lack of a statute search engine, Lord Justice Toulson made the Kafkaesque observation that “the courts are in many cases unable to discover what the law is”.¹⁴⁵

Although better legal databases and software can exist independently of algorithmic law, the necessity of these for functioning algorithmic law aids legal accessibility. That an individual can query facts and be issued with precise commands would make law significantly more accessible for those currently unable to navigate the complex network of statutes and case law. Whether this produces the same effect as “rules, easily learned and easily retained”¹⁴⁶ is unclear. Lord Mansfield might be dismayed at the deterioration of “common sense” principles, but perhaps also pleased that common sense no longer must be a necessary heuristic for legality, given the query-able ability of algorithmic law.

Freedom and Rights

The second critique of algorithmic law offered relates to individual freedom and rights. The purpose of algorithmic law is to guide individuals (through precisely calibrated rules and sanctions) to make choices that align with an overarching societal goal. In this way, algorithmic law can constrain an individual’s freedom: by tying outcomes to the behavioural predictions of other similar individuals; and by the past choices made by the individual themselves.¹⁴⁷ Wright and De Filippi describe such a system of law as limiting the “realm of choices” available to an individual and presenting the “illusion of free will”.¹⁴⁸

1 Subjugation of Freedom to the Majority Interest

The algorithmic narrowing of law subjugates individual freedom to the majority interest — a point best explained through an analysis of rights. Rights are the mechanism that entitles individuals to freedom, whether this be the privilege to act in a certain way, the power to exercise authority or a passive entitlement to be free from interference by others.¹⁴⁹ Law, then, is the means of allocating rights across society.¹⁵⁰

Two competing ideas guide this allocation of rights: instrumental theories and status theories. Instrumental theories view law as “an instrument of social policy”, where rights are tools for optimising society-wide

144 *R v Chambers* [2008] EWCA Crim 2467.

145 At 28 as cited in Bingham, above n 96, at 42.

146 *Hamilton v Mendes*, above n 143, at 1214.

147 See Sunstein, above n 46, at 52.

148 Wright and De Filippi, above n 26, at 43–44.

149 Leif Wenar “Rights” (9 September 2015) Stanford Encyclopedia of Philosophy <<https://plato.stanford.edu>> at [2.1] and [4].

150 At [4].

objectives.¹⁵¹ Rights are justified because, in aggregate, they achieve good consequences. By contrast, status theories take a deontological perspective of rights. Law expresses rights that do not depend on instrumental value.¹⁵² Rights reflect some human characteristic — they exist because “people actually have them”.¹⁵³

An instrumental theory is presented in the work of John Stuart Mill, who viewed rights as tools that could be used to bring the greatest utility to society. For Mill, restrictions on freedom are justified according to the harm principle.¹⁵⁴ The sole justification for interference with freedom is “self-protection”: decisions that impose harm on others may be restricted by law.¹⁵⁵ Thus, for Mill, restricting freedom under the harm principle is consistent with freedom as a right as this maximises and upholds the aggregate freedom of individuals in society.

As algorithmic law is better calibrated than traditional law to the actual consequences of an act, it can better uphold the harm principle and optimise freedom in society. Those predicted to harmlessly perform a (previously) illegal act would be allowed to do so, while those who would legally impose harm on others would have to bear the precise costs of that harm.

However, algorithmic law can undermine the freedom of particular individuals in the way that it is tied to *predicted harms*. Even highly accurate predictions are generalisations that will not hold true for every individual.¹⁵⁶ A prediction that is 99 per cent accurate will statistically uphold the harm principle — minimising aggregate harm — and be efficient for lawmakers to act on, but it will also undermine the freedom of the one per cent whose decisions are wrongly predicted. People in that one per cent are then subjugated to the average of the group of people who have similar attributes.

It has been argued this subjugation already exists, to a greater extent, under normal rules that are uniformly applied. With these rules, a broader group is subject to a less accurate average:¹⁵⁷

...any default rule, impersonal or personalized, is statistical in nature because it assigns rights and duties to individuals according to the averaged preferences of an entire population or a subset of people. Personalized default rules are just a better proxy—based on more accurate statistics—for the preferences of the specific party.

While this is true, the full political and practical picture of algorithmic law must be considered.

151 Richard A Posner “Instrumental and Noninstrumental Theories of Tort Law” (2013) 88 Ind LJ 469 at 469.

152 At 469.

153 Warren Quinn *Morality and Action* (Cambridge University Press, Cambridge, 1993) at 173 as cited in Wenar, above n 149, at [6].

154 John Stuart Mill *On Liberty* (Yale University Press, New Haven, 2003) at 80.

155 At 80.

156 Porat and Strahilevitz, above n 5, at 1461.

157 At 1461–1462.

Politically, algorithmic law increases the potential for law to be more restrictive of individual freedom. First, this is because tailoring ensures that oppressive restrictions only apply to few individuals and will not affect many voters. But, secondly, the idea that an algorithm *determines* a labelled group to be *risky* — for example, suspected terrorists — adds legitimacy to oppressive restrictions. By tailoring laws to a denounced group, restrictions on freedom might become more politically palatable. For the majority of people determined to be in a group unaffected by restrictions on liberty, the law may appear to be working correctly.

Practically, algorithmic law can allow for restrictions on freedom that would otherwise be unable to exist. Consider an algorithmic law that heavily restricts property rights for those with a high propensity to commit theft. These rules would be undesirable to apply to the entire population — the effect on commerce would be severe. It is only through tailoring that such *carve outs* of property rights can be made, targeting thieves (and subjugating the rights of some wrongly identified people) while preserving the benefit of the right for the rest of society.

For an instrumental theorist, this subjugation is fine. If law tailored to predictions on aggregate reduces harm, it is of no concern that the freedom of some is subjugated. Under this conception, rights exist to the extent that they benefit the collective.

Yet the idea that algorithmic law allows seemingly fundamental rights to be so readily diced and repackaged across individuals is confronting. Instrumentalists might have a defence to this concern by adapting how the outcome is measured — for instance, by seeking other goals, like egalitarianism. However, the criticism is not defeated. It is only from a status theory perspective that a true defence to the optimisation of algorithmic law is raised.

Consider the contemporary status theory of Robert Nozick, viewing rights as grounded in individual liberty and the Lockean “state of nature”.¹⁵⁸ For Nozick, rights comprise a “moral space around an individual”, a boundary that is prohibited to be crossed.¹⁵⁹ The core assumption is that any “boundary crossing” infringement on rights can only be permitted if it is duly compensated.¹⁶⁰ This, it is observed, is particularly relevant for law made on the basis of risk. Nozick gives the example of a law prohibiting epileptics from driving to reduce the risk to other road users.¹⁶¹ Forbidding any particular person from driving “may not actually lessen the harm to others” — it is an assumption of risk made by a prediction of how a person might behave.¹⁶² Therefore, a person who faces restrictions imposed for reasons of risk ought to be compensated by those who benefit from that reduction of risk. For algorithmic law, the core assumption is the opposite. While it might be possible for a system of compensation, the assumed

158 See Robert Nozick *Anarchy, State, and Utopia* (Basic Books, New York, 1974) at 10–12.

159 At 57.

160 At 57–84.

161 At 78 and 79.

162 At 78.

position is that interference with rights is an entitlement of the lawmaker — a means to some optimal end.

Casey and Niblett view the potential for algorithmic law to “overreach” and restrict freedom as presenting “real concerns for individual autonomy”.¹⁶³ Traffic lights could “decide who goes first based on productivity”, and law might “dictate what a citizen is allowed to eat for breakfast”.¹⁶⁴ Laws might be founded on predictions made on the basis of genetic information.¹⁶⁵ However, Casey and Niblett argue this is an objection to “reckless lawmaking” rather than any feature of algorithmic law.¹⁶⁶ The reality is that such “reckless” law-making occurs only from within the view of the instrumentalist, optimised freedom that they are advocating. The functional optimisation of law leads down a dangerous path, warned as being potentially “totalitarian” by Wright and De Filippi.¹⁶⁷

As algorithmic law allows rights to be reshaped in new ways, there will be a greater role for status theorist protections of freedom. Something feels instinctively wrong with the state pre-emptively controlling behaviour (and making rights contingent) on the basis of a prediction. Such an approach undermines the very autonomy that rights are intended to preserve. As expressed by Quinn:¹⁶⁸

We think there is something morally amiss when people are forced to be farmers or flute players just because the balance of social needs tips in that direction. Barring great emergencies, we think people’s lives must be theirs to lead. Not because that makes things go best in some independent sense, but because the alternative seems to obliterate them as individuals.

2 *Freedom and Justice: the Tyranny of Past Decisions*

In addition to limiting the freedom of those affected by incorrect predictions, algorithmic law can limit freedom by ascribing high signalling value to an individual’s past decisions. Past choices take on a signalling value for algorithms that determine future law, and the costs of harmful decisions become disproportionate to the *actual* harm caused.

This is another form of subjugation to the majority.¹⁶⁹ A prediction made on the basis of an individual’s past choices requires assumptions about this behaviour to be made from the data of the past choices of others. However, where past choices determine future applicable law for an individual, this is also a justice concern.

The signalling value of an individual’s past actions acts as a sanction (or an incentive) for those actions. The dynamism of algorithmic law further means that the exact signalling value of any act will be indeterminate — an uncertainty which itself operates as a sanction. A prudent individual,

163 Casey and Niblett, above n 2, at 1443.

164 At 1443.

165 Ben-Shahar and Porat, above n 36, at 683–684.

166 At 52.

167 Wright and De Filippi, above n 26, at 43.

168 Quinn, above n 153, at 171.

169 I discussed this above in terms of rights.

realising the potential for a decision to restrict future options in unforeseen ways, will choose the *safer* option to reduce the risk of negative signalling.

From an instrumentalist viewpoint of rights this is mostly fine. The ongoing freedom of an individual *ought* to be limited by the signalling value of the individual's previous decisions, because, on aggregate, this achieves good outcomes. Risky people should face more legal restrictions. There may be some concern that the indeterminacy of algorithmic law will make individuals overcompensate and be too cautious; however, this can be offset in the calculation of the signalling value itself. There will also be some need to encourage risky behaviour where there is a corresponding utility — for example, by limiting the extent that a bankruptcy can be used for signalling, to not deter individuals from starting a business.

However, a status perspective of rights would see law made on the basis of signalling as being an uncompensated interference with rights — a punishment (or reward) for past decisions that is disproportionate to such decisions. This is best explained with reference to corrective justice.

Corrective justice is a theory of justice in private law which maintains that a wrong creates a transactional inequality in rights and establishes a relationship between the wrongdoer and the wronged.¹⁷⁰ Such a view of justice then mandates restoring the original equality between parties by correcting the imbalance in rights — restoring the wronged party to their rightful position.¹⁷¹ Corrective justice subscribes to a status theory of rights. Rights are deontological. They are a Kantian unification of free individuals in society — the “sum of the conditions under which the choice of one can be united with the choice of another in accordance with a universal law of freedom”.¹⁷² The pure, personal rectification of a transactional inequality under corrective justice does not take place when a wrong is also used to signal more restrictive laws into the future. For example, the sanction for a breach of tort becomes the cost of putting the victim back in the same position *and* the cost of future, more restrictive laws.

When future sanctions are prescribed from past decisions, “feedback loops” that further narrow individual freedom can occur. Feedback loops can be explained by reference to social media “echo chambers”, in which a person is narrowed into only seeing similar views to their own.¹⁷³ An algorithm takes a person's past information — the content they interact with, their friend group, the news sources they read — and predicts their interests. It then presents back an “informational universe that is entirely self-selected”, further narrowing content choices into the future.¹⁷⁴ O'Neil gives an example of a feedback loop that is created when employers use credit score algorithms to evaluate potential employees.¹⁷⁵ Individuals with low

170 Ernest J Weinrib *The Idea of Private Law* (Oxford University Press, Oxford, 2012) at 62–63.

171 Ernest J Weinrib “Corrective Justice in a Nutshell” (2002) 52 UTLJ 349 at 349.

172 Immanuel Kant *Die Metaphysik der Sitten* (1797) (translated ed: Mary Gregor (translator) *The Metaphysics of Morals* (Cambridge University Press, Cambridge, 1996)) at [6:230].

173 Cass R Sunstein *Republic.com 2.0* (Princeton University Press, New Jersey, 2007) at 43–44.

174 Sunstein, above n 46, at 50.

175 O'Neil, above n 4, at 7.

credit scores are less likely to find work, making it even harder for them to improve their credit score.¹⁷⁶

It is not difficult to see how algorithmic law can then also have this effect. Consider Uber, a personal driving service where passengers rate their driver. A driver falling below a particular average will have their account deactivated.¹⁷⁷ Similar scoring models could be widely implemented in law. For example, imagine a rating system for surgeons (combining objective surgery results with patient feedback), where a surgeon with a low rating is restricted to performing low-risk surgeries. This system would be beneficial for patients, who would, on aggregate, face less risk. However, a surgeon with a low rating would have a reduced opportunity to gain experience — actively preventing them from increasing their rating in the future.

Under such a system, the costs of making the wrong choice can become exponentially high and disproportionate to the harm caused. These concerns are reflected in criticisms of risk-based sentencing — that certain groups in the community can be marginalised.¹⁷⁸ A person who makes a bad decision will not only bear the retributive consequences for that decision, but suffer consequences from the signalling value about the *kind of person* they are, sent to algorithms that affect their life. We might accept this for insurance,¹⁷⁹ but to what extent is this acceptable in law? The law might move from a general position of proportional consequences to a position of harsh limitations on freedom for some, because of how it has been signalled they will act.

To some degree, a right to be free of the past is inherent in freedom. Individuals need to face consequences for their decisions, but in a proportional manner that allows them the opportunity to move on and make different decisions. It was this idea that saw the enactment of the Criminal Records (Clean Slate) Act 2004 to recognise that, after seven law-abiding years, some past convictions ought to be hidden from the record. As stated by Hon Phil Goff in the parliamentary debates, these people “have met the penalty that was imposed on them” and “should be given a fair go to put that offending behind them”.¹⁸⁰ Ideas like corrective justice have a role to play in the proliferation of algorithmic law — ensuring that consequences for actions remain proportionate and are not entirely functional to advance some wider, unrelated goal.

176 At 7.

177 “Driver Deactivation Policy - Australia & New Zealand Only” (28 June 2016) Uber <www.uber.com>. Uber only look to the most recent 500 trips to give the driver “the chance to improve [their] rating over time”.

178 Discussed at the beginning of Part V.

179 See Human Rights Act 1993, s 48. We might equally not accept this for insurance!

180 (4 May 2004) 617 NZPD 12566.

VI CONCLUSION

Algorithmic law might be viewed as law and economics taken to the furthest extent. It is the optimisation of function, enabled by technology. Such optimisation inevitably calls for an appraisal of the legal values it might subvert. To what exact societal cost should rights be protected for any one individual? What is the extent of permissible inequality before the law?

Such questions go to the very heart of legal philosophy and cannot be easily answered. Rather, this article has attempted to define algorithmic law as a discrete category of law — and to reconcile the different scholarship advocating for this law. It has then, against the background of arguments in favour of algorithmic law, presented preliminary critiques of algorithmic law with reference to normative values of rule of law and freedom.

Robin Paul Malloy describes the law and economics theory of wealth maximisation as “analogous to the Frankenstein Monster”.¹⁸¹ It can “lead even the most noble and good spirited people to conclusions that affront our basic social values” — an observation accepted by Posner, who observed that moral concerns may override wealth maximisation (but that moral philosophy was a “weak field” unable to obtain consensus).¹⁸² For Malloy, the values of freedom, liberty and human dignity are important, and “something more than the cold hard variables of economic calculus”.¹⁸³

While economics, capitalism, and democracy are all important factors in helping us understand and promote human dignity, we cannot escape our own personal moral obligation to make each of these factors subservient to the higher values they can promote ... freedom, liberty, and human dignity.

With algorithmic law, the usual assumptions that restrain the wealth-maximisation of law and economics do not apply. It becomes possible for efficient law to be made by personalising rules to each individual. Laws can be far more intrusive on human autonomy and channel a person down a path of restricted choices. Laws can undermine aspects of law that might have previously been unconsciously assumed as inherent.

Because of this, it will be important to sometimes place “higher values” above “cold hard” outcome-producing variables. This is a view well expressed by the following quote from Milton Friedman:¹⁸⁴

A free society, I believe, is a more productive society than any other; it releases the energies of people, enables resources to be used more effectively, and enables people to have a better life. But that is not why I am in favor of a free society. I believe and hope that I would favor a free

181 Robin Paul Malloy and Jerry Evensky *Adam Smith and the Philosophy of Law and Economics* (Kluwer Academic Publishers, Dordrecht, 1995) at 160.

182 At 160 and 170.

183 At 160.

184 Milton Friedman “Free Markets and Free Speech” (1987) 10 Harv JL & Pub Poly 1 at 7 as cited in Malloy and Evensky, above n 181, at 160.

society even if it were less productive than some alternative—say, a slave society. ... I favor a free society because my basic value is freedom itself.

There are areas of law where algorithmic law might readily undermine core values and be undesirable. Criminal law is one example. In other areas, such as regulatory law, algorithmic law might be more appropriate. However, as this article has argued, algorithmic law should be approached with caution. That there is significant potential for society to benefit from efficient, predictive law should not mean that the master of statistics and economics can reduce to a mere number the higher values that law can promote.