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The ‘rule of law’ implications of data-driven decision-making: a techno-regulatory perspective

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ABSTRACT

Techno-regulation is a prominent mechanism for regulating human behaviour. One type of techno-regulation concerns automated decision-making with legal effects. While automated decision-making (ADM) systems in the public domain have traditionally been based on conscious design of decisional norms, increasingly, Data Science methodologies are used to devise these norms. This data-driven approach causes frictions with the underlying principle of public-sector decision-making, namely adherence to the rule of law. In this paper we discuss three major challenges data-driven ADM poses to the Rule Law: law as a normative enterprise, law as a causative enterprise and law as a moral enterprise.

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KEYWORDS Techno-regulation; automated decision-making; rule of law

1. Introduction

Since the industrialisation, we have witnessed an influx of novel artefacts, objects, and more recently automated systems that come to play a significant role in what we do, how we perceive and interpret the world, how we make our choices, and under what conditions.¹ We have entered an era in which algorithmic systems based on Big Data capitalise economic and institutional power with profound effects on the allocation of resources owing to their capacity to control and manage processes.² We see the emergence of ‘algorithmic authority’ as the legitimate power of ‘code’ to direct human action and also to impact which information is considered true.

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¹Paul Verbeek, *What Things Do – Philosophical Reflections on Technology, Agency, and Design* (Robert P Crease, tr) (The Pennsylvania State University Press, 2005).

²Michael Latzer and others, ‘The Economics of Algorithmic Selection on the Internet’ (Working Paper, University of Zurich, 2014): http://www.mediachange.ch/media/pdf/publications/Economics_of_algorithmic_selection_WP_.pdf. For more on Big Data and media/information economics, see C Argenton and J Prüfer ‘Search Engine Competition with Network Externalities’ (2012) 8 *Journal of Competition Law & Economics* 73.

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Issues surrounding (big) data analytics and automated decision-making (ADM), such as those touching on privacy and data protection, have been widely studied, but the enabling and restricting role of data-driven solutions as techno-regulatory orders have remained mostly unanalysed.³ Although studies on techno-regulation frequently analyse and characterise technology for its normativity⁴, research theorising the regulatory relevance of Big Data analytics as a normative order in itself is much sparser.⁵ As the world of data has become the test bed for social sciences, economic innovation and state administration, the need for research explaining and framing the regulatory dimension of the data-driven practices is ever more critical.

This article contributes to this venture. It departs from the premise that data-driven ADM processes, governed by complex algorithms, are either embodiments of existing normative orders, or they themselves enact *ad hoc* regulatory orders with or without a legal basis. In terms of regulatory constraints and capacities, data-driven ADM systems go much beyond existing legal decision-making based on codified legal norms. Although both types of systems (data-driven *versus* code-driven as Mireille Hildebrandt calls them⁶) regulate human behaviour, their assessment from a rule of law perspective is different. In fact, data-driven ADM systems undermine the rule of law and hence, developers, lawyers and subjects of decisions by these systems should pay attention.

The paper is organised as follows. First, in Section 2, we revisit techno-regulation as a mechanism to regulate human behaviour and describe how conscious implementation of norms is being augmented or replaced by norms derived from data analytics. Next, in Section 3, we discuss some shortcomings and effects of this turn towards data-driven ADM. Section 4 addresses the challenges that these shortcomings cause for the rule of law as the backbone of legal decision-making. Section 5 concludes the paper with some reflections and a call for action.

2. A new horizon of techno-regulation: big data automated decision-making

Left to itself, cyberspace will become a perfect tool of control.⁷

³A recent remarkable exception is Timothy D Robinson, 'A Normative Evaluation of Algorithmic Law' (2017) 23 *Auckland University Law Review* 293.

⁴See Lawrence Lessig's *Code and Other Laws of Cyberspace* (Basic Books, 1999) and the descendant literature; WN Houkes, 'Rules, Plans and the Normativity of Technological Knowledge' in MJ de Vries and others (eds), *Norms in Technology* (Springer Science+Business Media Dordrecht, 2013).

⁵M Hildebrandt, 'Law at a Crossroads: Losing the Thread or Regaining Control? The Collapse of Distance in Real Time Computing' in Morag Goodwin, Bert-Jaap Koops and Ronald Leenes (eds), *Dimensions of Technology Regulation* (Wolf Legal Publishers, 2010) 165; Mireille Hildebrandt and Bert-Jaap Koops, 'The Challenges of Ambient Law and Legal Protection in the Profiling Era' (2010) 73 *MLR* 428.

⁶Mireille Hildebrandt, 'Algorithmic Regulation and the Rule of Law' (2018) 376 *Philosophical Transactions of the Royal Society A*, doi:10.1098/rsta.2017.0355.

⁷Lawrence Lessig, *Code and Other Laws of Cyberspace v.2.0* (Basic Books, 2006) 6.

As the world we are living in becomes densely populated with coded objects, it seems almost ‘axiomatic’ that the environment and artefacts possess certain governance mechanisms which steer behaviour both at the individual and institutional level – by facilitating or imposing some forms of use and conduct, while inhibiting others.⁸ Some have even claimed that technology is law.⁹ In a literal sense this is not correct, because law, or legal regulation, is enacted by the legislator and the public bodies that act on the basis of competences attributed by the constitution or the legislator itself.¹⁰ When regulation is taken in the broadest sense to mean intentional influencing of behaviour to produce certain identified outcomes – brought into effect either by code, laws, self-regulation, or by various private schemes¹¹ – it becomes clear that, from a functional standpoint, both technology and Law may act as regulatory mechanisms which seek to subject human conduct to the governance of certain rules.¹²

Regulation so defined is conceptually closer to the usage in biology, systems theory and cybernetics – encompassing almost any control apparatus or procedure.¹³ In fact, Murray and Scott bring control theory into the analysis of regulation. Not only should we be aware of the different modalities of regulation, elaborating on Lessig’s famous four (law, norms, market, code), but also that there are three elements necessary to generate a control system: standard-setting, information gathering, and behaviour modification.¹⁴

⁸This, in fact, is not a new realisation. Jeremy Bentham already in 1787 wrote ‘Morals reformed ... the gordian knot of the poor-law not cut, but untied – all by a simple idea in Architecture’, Panopticon in: Mairan Booi (ed), *The Panoptic Writings* (London: Verso, 2011) 29–95.

⁹Langdon Winner, *Of Autonomous Technology: Technics-Out-of-Control as a Theme in Political Thought* (The MIT Press, 1977) 323–25. Also see Langdon Winner, ‘Do Artifacts Have Politics?’ (1980) 109(1) *Daedalus* 121. Lessig (n 7) 6.

¹⁰This is what the rule of law is about. About the ‘legal’ interpretation of code, see for instance L Asscher, ‘“Code” as Law. Using Fuller to Assess Code Rules’ in Egbert Dommering and Lodewijk Asscher (eds), *Coding Regulation – Essays on the Normative Role of Information Technology* (TMC Asser, 2006) 61–90.

¹¹Julia Black, ‘Critical Reflections on Regulation’ (2002) 27 *Australian Journal of Legal Philosophy* 1; Ronald Leenes, ‘Framing techno-regulation: an exploration of state and non-state regulation by technology’ (2011) 5 *Legisprudence* 147; Ian Brown and Chris Marsden, *Regulating Code. Good Governance and Better Regulation in the Information Age* (Cambridge, MA, London: MIT Press, 2013). For more on ‘regulation’, see Roger Brownsword and Morag Goodwin, *Law and the Technologies of the Twenty-First Century. Text and Materials* (Cambridge University Press, 2012); J Kooiman (ed), *Modern Governance* (London: Sage, 1993); C Hood, *The Tools of Government* (London: Macmillan, 1983). For the range and scope of different definitions of regulation, see Lyria Bennett Moses ‘How to Think about Law, Regulation and Technology: Problems with “Technology” as a Regulatory Target’ (2013) 5 *Law, Innovation and Technology* 1.

¹²Hans Kelsen, ‘The Law as a Specific Social Technique’ (1941–42) 9 *University of Chicago Law Review* 75, 79.

¹³Christopher Hood and others, *The Government of Risk: Understanding Risk Regulation Regimes* (Oxford University Press, 2001).

¹⁴A Murray and C Scott, ‘Controlling the New Media: Hybrid Responses to New Forms of Power’, (2002) 65 *MLR* 491, 500. Also, see Andrew D Murray, ‘Conceptualising the Post-Regulatory (Cyber)state’ in Roger Brownsword and Karen Yeung (eds), *Regulating Technologies* (Hart, 2008) 292.

Techno-regulation refers to the intentional influencing of individuals' behaviour by embedding norms into technological systems and devices.¹⁵ Depending on the context, such regulatory models may interchangeably be referred to as: 'regulation by technology', 'technological normativity', 'regulative software', 'law as design', 'design-based regulation' or 'algorithmic regulation'. Techno-regulatory settings may focus on products/services, places or persons covering a complex plethora of practices and designs. Today, we commonly experience these in driving controls in cars, internet filtering, Digital Rights Management systems, speed bumps, personalised information services, etc. Increasingly, techno-regulation also finds its way in systems that take decisions about individuals and create legal effects.

Vast amounts of raw data compiled from various sources (eg communication networks, the energy grid, and transportation and financial systems) in every realm of life are put to use in order to obtain actionable information for the purposes of detecting of fraudulent transactions, calculation of credit-worthiness, organising of Facebook newsfeed and so on. Apparently, our society is heavily dependent on databases and analytic tools to carry out processes of various kinds and scale. Although data-driven practices have long made their way into our lives through statistics and actuarial methods (since at least the nineteenth century¹⁶), what is happening now is the intense and exponential expansion of these practices by means of the methodologies conceptualised under the term 'big data analytics'. Computational operations for abstraction, correlation, classification, pattern recognition, profiling, modelling, and visualisation are used in a functional way to extract signals from noise in large bodies of data so that those signals can serve as data representations for classifying persons, events or processes.¹⁷ These representations (and profiles) are then used to control processes and make decisions.¹⁸

¹⁵Van den Berg and Leenes emphasize and draw attention to other less 'legal' forms of influencing behaviour such as persuasion, or nudging. See Bibi van den Berg and Ronald Leenes, 'Abort, retry, fail: scoping techno-regulation and other techno-effects', in Mireille Hildebrandt and Jaenne Gakeer (eds), *Human Law and Computer Law: Comparative Perspectives* (Springer, 2012). They argue, at 74, that 'persuasion, nudging and affording are more subtle, yet clearly intentional, forms of affecting human behaviour, through the use of technologies, which are overlooked in the current debate on techno-regulation'.

¹⁶See for instance, Alain Desrosieres, *The Politics of Large Numbers: A History of Statistical Reasoning* (Camille Naish, tr). Originally published as *La politique des grands nombres: Histoire de la raison statistique* (Editions La Decouverte, 1993).

¹⁶See for instance, Alain Desrosieres, *The Politics of Large Numbers: A History of Statistical Reasoning* (Camille Naish, tr). Originally published as *La politique des grands nombres: Histoire de la raison statistique* (Editions La Decouverte, 1993).

¹⁷Jerry Kaplan, *Humans Need Not Apply, A Guide to Wealth and Work in the Age of Artificial Intelligence* (Yale University Press, 2016) 25.

¹⁸KEC Levy, 'Relational Big Data' (2013) 66 *Stanford Law Review Online* 73, n.3; Viktor Mayer-Schönberger and Kenneth Cukier, *Big Data: A Revolution That Will Transform How We Live, Work, and Think* (Houghton Mifflin Harcourt Publishing Company, 2013).

Data analytics has become a method of empirical inquiry, performed on informational sources to extract new insights out of raw data, supplementing or even substituting the conscious design of rules to control processes and decisions; thus moving from causation as the link between input and output to correlation.¹⁹ Conceptualising big data as a methodology – rather than as a computational source/tool/instrument defined with reference to size and speed – provides a framework which enables the analysis of the regulatory aspects of data-driven methodologies, and the ensuing rule of law implications that will be elaborated in the following parts of this paper.

Regulation, standard-setting, monitoring and behaviour modification by means of computational algorithms is nothing new.²⁰ Governmental bodies have used algorithms in decisional processes since the dawn of the computers. Levying taxes, and more generally, the social welfare state, would not be possible without these automated decision systems.²¹ The way legislation is transformed into executable code is what is new.

One classical approach has been to represent state-of-the-art domain knowledge in production rules (if-then rules), and then have an inference engine reason on these to give expert-like advice or make decisions.²² In many of these legal knowledge based systems (LKBS) – a relatively successful type of rule-based application – developers represented ‘the law’ in executable form. This allowed the systems to make correct legal decisions and be able to explain or legally justify their reasoning process together with the conclusions they reached.²³ The developers of such systems aimed at faithfully representing the authoritative legal source in the domain of application as well as the anticipated kinds of cases relevant to the domain (and rule-based representations of existing case law).

This approach, however, never really caught on substantially. Quite apart from requiring significant effort to represent legal rules, which affected the adoption of this methodology of building (A)DM systems, there are also

¹⁹Michael Mattioli, ‘Disclosing Big Data’ (2014) 99 *Minnesota Law Review* 538.

²⁰Cf. Hildebrandt (n 6) 2.

²⁰Cf. Hildebrandt (n 6) 2.

²¹While we focus on automated decision systems, in the end the same reasoning applies to advice giving systems. See Hildebrandt (n 6); Jason Millar and Ian Kerr, ‘Delegation, Relinquishment and Responsibility: The Prospect of Expert Robots’, in Ryan Calo, Michael Froomkin and Ian Kerr (eds), *Robot Law* (Edward Elgar, 2016) 102–28, on the inevitability of relinquishing control to machines.

²²These types of systems have been in operation since the 1970s. See for instance, EA Feigenbaum, ‘The Art of Artificial Intelligence: I Themes and Case Studies of Knowledge Engineering. Technical Report’ (UMI Order Number: CS-TR-77–621, Stanford University, 1977); Andrew Stranieri and John Zelezniok, *Knowledge discovery from legal databases* (Springer, 2010).

²³‘Not necessarily through mimicking the actual reasoning process, but by, for instance, implementing the underlying (complex) legal rules and executing those’. Trevor Bench-Capon, ‘Exploiting isomorphism: development of a KBS to support British coal insurance claims’, *Proceedings of the 3rd International Conference on Artificial Intelligence and Law*, New York, 1991, 62–68; Jörgen Svensson ‘Legal expert systems in general assistance: from fearing computers to fearing accountants’ (2002) 7 *Journal of Information Polity* 143. Also, on the failures of LKBS, see P Leith, ‘The rise and fall of the legal expert system’ (2010) 1 *European Journal of Law and Technology* (Issue 1).

fundamental problems due to the intentional open-texturedness and vagueness of the human language through which the law is expressed. Moreover, the application of legal rules is highly context dependent, meaning that the fringes of what such a regulatory mode appropriately handles are easily reached.²⁴ The LKBS approach is limited due to the difficulty of dealing with fundamental characteristics of legal norms (open-texture, vagueness)²⁵ and its inherent difficulty to cope with the dynamics of the domain it purports to govern.²⁶ A further complication is that many, if not all, domains in which legal decisions are taken are characterised by a combination of ‘positive’ law and ‘case’ law.²⁷ The rule-based LKBS approach, due to its rule based nature, has difficulty in coping with dynamic case law.

Owing to the advances in the fields of data analytics, semantic web and Natural Language Processing (NLP), data-driven ADM systems are now beginning to assign meaning to vague terms, and ‘interpret’ normative standards, and principles to ‘manage’ the uncertainties of the human language by deriving knowledge from a large legal corpus including the case law.²⁸ Modern techniques could potentially overcome the static (and limited) nature of the classical rule-based LKBS because of their adaptive capacities and affordances. Rule-based (code-driven) systems, by incorporating data analytics capabilities, may mitigate the rigidity of pre-set architectures – implementing norms by way of incorporation of new knowledge through (machine) learning and feedback mechanisms and thus become data-driven.

Since techno-regulation is defined as the effectuation of norms through technical means at various levels such as rule-making, implementation, monitoring and enforcement in a normative system, the intrinsic regulatory capacity of data-driven ADM is evident. We see the regulative force of data analytics in almost every context where operation or conduct of certain activity is, either fully or partially, automated or controlled by algorithmic decision-making systems.²⁹ The predictive and the pre-emptive nature of

²⁴Lyría Bennett Moses and Janet Chan, ‘Using Big Data for Legal and Law Enforcement Decisions’ (2014) 37 UNSWLJ 643, 657.

²⁴Lyría Bennett Moses and Janet Chan, ‘Using Big Data for Legal and Law Enforcement Decisions’ (2014) 37 UNSWLJ 643, 657.

²⁵Abdul Paliwala, ‘Rediscovering artificial intelligence and law: an inadequate jurisprudence?’ (2016) 30 *International Review of Law, Computers & Technology* 107; Philip Leith ‘The Rise and Fall of the Legal Expert System’ in Abdul Paliwala (ed), *A History of Legal Informatics* (Prensas de la Universidad de Zaragoza, 2010) 179–203.

²⁶See Ronald Leenes, ‘Hercules of Karneades: Hard cases in recht en rechtsinformatica’ (Universiteit Twente, 1999) (in Dutch).

²⁷We put positive law and case law in quotes to signify that both sources are not limited to material produced by the legislative and judicial branches of government. Rather, we mean authoritative rules that are adjudicated (or enforced) by some agency that has the authority to do so.

²⁸See Kevin Ashley, *Artificial Intelligence and Legal Analytics – New Tools for Law Practice in the Digital Age* (Cambridge University Press, 2017).

²⁹Karoline Krenn, ‘Markets and Classifications – Constructing Market Orders in the Digital Age: An Introduction’ (2017) 42(1) *Historical Social Research* 7, 15: <http://dx.doi.org/10.12759/hsr.42.2017.1.7-22>.

data analytics amplify both the direct and indirect regulative impact of the ICTs.³⁰

The resulting systems could take the form of a combination of classical, including handcrafted, rule-based representations augmented with knowledge derived by Machine Learning (ML). In any case, these systems are capable of dynamically adapting to their environment owing to the complex data-driven knowledge bases that are not directly intelligible.

3. Data-driven ADM concerns, challenges and potential harms

Data-driven ADM processes, governed by algorithms of varying degrees of complexity are either the embodiment of existing normative orders, or they themselves enact *ad hoc* regulatory orders with or without legal basis such as the case of online advertising where algorithms decide who is worthy of receiving a discount, or the call service using sentiment analysis to decide which of the callers is more tolerant to be kept waiting.³¹ Although such trivial practices may seem irrelevant from the legal perspective, a second thought reveals several repercussions with regard to consumer rights and human dignity in general.

It should also be borne in mind that there are secondary effects. ADM does not necessarily involve decisions directly about the individuals. For instance, a simple ML application to recognise congestion on visual data (eg from a traffic surveillance camera) may give rise to biased decisions with regard to traffic flow, depending on the data and the way of processing. One other dimension is that nothing comes for free, that is, the efficiency gains or other benefits to be derived from data analysis also have trade-off effects in other domains or for other individuals. Cutting costs through data analysis could mean certain economic and material diversions, and a shift of interests among employees, students, citizens or consumers. For instance, reducing the cost of handling customer complaints through a techno-regulatory application (eg automated classification and diverting of complaints to the relevant departments) may give rise to a significant change in a company's way of communicating with the public. Moreover, such systems – though not necessarily intentionally – run the risk of favouring certain type of complainants against others without any just cause. Or, a bank which decides to use predictive analytics to prevent customer churn can act pre-emptively such as to offer advantageous services to the customer who is regarded to be more likely to move to another bank. This may seem to be a discriminatory result in that many of us would not consider risk of churn as a legitimate basis on the side of the bank to differentiate between the service receivers.

³⁰Ian Kerr and Jessica Earle, 'Prediction, Preemption, Presumption: How Big Data Threatens Big Picture Privacy' (2013) 66 *Stanford Law Review Online* 65.

³¹Luke Dormehl, *The Formula: How Algorithms Solve All Our Problems and Create More* (WH Allen, 2015).

ADM, when coupled with data analytics, acquires the necessary adaptive capability to diffuse into more general domains controlling and regulating real-life events that are of relevance to law and to the legal system.

The emergence of ‘algorithmic regulation’ legitimises the power of the ‘code’ to direct human action. But with this, the risks of epistemological flaws and biases inherent to machine learning enter the scene. These may raise concerns as to fairness/non-discrimination, privacy/invasiveness, and the notions of the ‘autonomous self’ and dignity.

Machine learning is a problem-solving approach which implements statistical learning theory as a framework of computational strategies for discovering ‘truth’ in empirical questions. Data mining employs quantitative and inductive methods (equations and algorithms), along with statistical testing to process data resources with a view to identifying reliable patterns, trends, and associations among variables that describe and/or anticipate a particular process or event. What can be derived from the data is determined by what is in the data, what the system designers label as the relevant factors to be analysed, and the adopted methodologies. For instance if the training dataset for predicting court decisions consists of case law, a relevant question is *which* cases are incorporated in the corpus. Does it feature all decided cases or only those that were published (and hence selected by an editorial board)? What material related to the case is taken into account? All files, or only the judgment? In the latter case, one has to be aware that the facts may be formulated to align with the conclusion reached in the case.³²

Data are not capable of verifying the assumptions and the perspective underlying a certain inference of causation. So, letting data speak for itself thus is problematic in many ways. Algorithms in machine learning are not immune from the general shortcomings of the causal inference in large data sets. Data mining reveals correlation, not causality, which could be spurious, and this brings in the question of the ethical justifiability of acting upon them.³³ In order to establish a causal link, patterns need models with an encompassing narrative since ‘it is one thing to establish significant correlations, and still another to make the leap from correlations to causal attributes’.³⁴ As an inductive method – progressing from particular cases

³²N Aletras and others, ‘Predicting judicial decisions of the European Court of Human Rights: a Natural Language Processing perspective’ (2016) *PeerJ Computer Science* 2:e93 <https://doi.org/10.7717/peerj-cs.93>, cited in Hildebrandt (n 6).

³³‘Episcopalians dog owners who drive more than forty miles to work and recently moved to the suburbs may have an extraordinarily high rate of bladder cancer, but so what? The correlation is probably spurious. Nothing about dog ownership, being Episcopalian, or recently moving to the suburbs would seem to cause bladder cancer. The challenge is to sort through all of the correlations and decide which have a causal basis’, Scott E Page, *The Difference: How the Power of Diversity Creates Better Groups, Firms, Schools, and Societies* (Princeton University Press, 2008) 85.

³⁴David Bollier, ‘The Promise and Peril of Big Data’ (Aspen Institute) 2010, 16.

(sample data) – machine learning accumulates a set of discovered dependencies, correlations or relationships that are referred to as ‘model’. Although a model in the abstract may be robust and consistent, it may nevertheless be favouring certain values, persons, or processes – bringing us to a domain which is more political, rather than being scientific.³⁵

A well cited example of legal analytics that indirectly shows bias and epistemological flaws is the study performed by Roger Guimerà and Marta Sales-Pardo, who devised a model to predict a justice’s vote (in the US Supreme Court) based on the other justices’ votes in the same case.³⁶ The model predicts votes more accurately (83%) than human experts. However, the model does not take into account the content of the case, but only ‘metadata’. In another often cited study, researchers built a model to predict the outcomes of the 2002 Term. Again, the system outperformed (with 75% accuracy) expert predictions. And again, no information about the case or applicable law was incorporated in the model. Instead, features like the name of the judge, the term, the issue, the court of origin and whether oral arguments were heard were used.³⁷ Both studies illustrate how the normative force of the law – that was present in code-driven systems – becomes replaced by the patterns in a (historic) dataset that may have nothing to do with legal norms.

4. The rule of law implications

Technology is never neutral,³⁸ yet in the eyes of many, technology and politics are separated in that politics is supposedly based on values, while technology thrives on scientific knowledge and objective facts.³⁹ It propagates an interpretation of regulation from an external perspective, which focuses on behavioural modification (by any means), while neglecting the internal perspective that deals with checks and balances of the rule of law. An apparent result of such dualism is the lack of democratic control over much techno-regulation. Whereas law is created in the public domain, techno-regulation (even when adopted by ‘the state’) often is not.⁴⁰ Yet, techno-regulation

³⁵Lucas Introna, and Niall Hayes ‘On Sociomaterial Imbrications: What plagiarism detection systems reveal and why it matters’ (2011) 21 *Information and Organisation* 107, 108.

³⁶R Guimerà and M Sales-Pardo ‘Justice Blocks and Predictability of U.S. Supreme Court Votes’ (2011) *PLoS ONE* 6(11): e27188. <https://doi.org/10.1371/journal.pone.0027188>.

³⁷Theodore W Ruger and others, ‘The Supreme Court Forecasting Project: Legal and Political Science Approaches to Predicting Supreme Court Decisionmaking’ (2004) 104 *Columbia Law Review* 1150.

³⁸Mireille Hildebrandt, ‘A Vision of Ambient Law’ in Roger Brownsword and Karen Yeung (eds), *Regulating Technologies* (Hart, 2008) 175–92; Winner, ‘Do Artifacts Have Politics?’ (n 9).

³⁹A Feenberg, ‘Critical Theory of Technology’ in JKB Olsen and others (eds), *A Companion to the Philosophy of Technology* (Blackwell Publishing, 2009) 149. Also see M Bunge, *Evaluating Philosophies* (Science +Business Media Dordrecht, 2012) 5.

⁴⁰Leenes, ‘Framing Techno-Regulation’ (n 11) 147–48.

should be situated in a wider framework encapsulating the mutual entanglements between culture, politics and technology. As Don Ihde has put: ‘technological form of life is part and parcel of culture, just as culture in the human sense inevitably implies technologies’.⁴¹ Or, as Andrew Feenberg writes ‘Technology should be brought into the public sphere where it increasingly belongs’.⁴²

Every legal system has a claim to legitimacy in the sense that the source of authority relies on a moral right to rule.⁴³ In modern democratic systems, the principle of the rule of law, as an essential pillar of this moral dimension, requires that rules are publicly declared with prospective application, and possess the characteristics of generality, equality, and certainty.⁴⁴ As the protection of rights, prevention of arbitrariness and holding the state responsible for unlawful acts are only possible in an intelligible, reliable and predictable order, universality and relatively constant application over time in a prospective and non-contradictory way may be regarded as the main constituents of the notion of rule of law.⁴⁵ Rights are of little use if their limits and proper scope are not in advance known by citizens.

An important procedural dimension of the rule of law, which is of particular concern from the ADM perspective, is the effective capability to contest decisions.⁴⁶ This primarily requires that one must be aware of the existence of an ADM process, and also foresee and understand the consequences.⁴⁷ Law’s capacity to allow subjects to contest judicial and administrative decisions, including the validity of the rule itself, provides a meta-level procedural safeguard in that ‘the addressees and the “addressants” of legal norms coincide’ – a form of self-regulation where the law maker is bound by the rules of its own creation.⁴⁸

Against this backdrop, we conceptualise three potential harms of data-driven techno-regulation which undermine the rule of law as a procedural safeguard to discern, foresee, understand and contest decisions – namely (i) the collapse of the normative enterprise (ii) the replacing of a causative basis with correlative

⁴¹Don Ihde, *Technology and the Lifeworld. From Garden to Earth* (Indiana University Press, 1993) 20.

⁴²Feenberg (n 39).

⁴³Or as Thomas Hobbes might have put it, how is authority now authorized? Zygmunt Bauman and others, ‘After Snowden: Rethinking the Impact of Surveillance’ (2014) 8 *International Political Sociology* 121.

⁴⁴Brian Tamanaha, *On the Rule of Law* (Cambridge University Press, 2004).

⁴⁵Jeremy Waldron, ‘The rule of law in contemporary liberal theory’ (1989) 2 *Ratio Juris* 84; Hans-Wolfgang Arndt, ‘Das Rechtsstaatsprinzip’ (1987) 27 *JuS* L41–L44.

⁴⁶Speaking of natural overlaps between the substantive and procedural aspects of the rule of law, Waldron mentions that a hearing by an impartial tribunal acting on the basis of the evidence and arguments presented, a right to hear reasons from the tribunal when it reaches its decision, and some right of appeal to a higher tribunal as procedural characteristics are equally indispensable. Jeremy Waldron, ‘The Rule of Law and the Importance of Procedure’, in James E Fleming (ed), *Getting to the Rule of Law* (New York University Press, 2011) 7.

⁴⁷M Hildebrandt, ‘Profile transparency by design? Re-enabling double contingency’ in M Hildebrandt and K de Vries (eds), *Privacy, Due Process and the Computational Turn* (Routledge, 2013).

⁴⁸Mireille Hildebrandt, *Smart Technologies and the End(s) of Law* (Edward Elgar, 2015) 10.

calculations, and (iii) the erosion of moral enterprise.⁴⁹ The informational asymmetries, flawed epistemology of data-driven inferences together with the bias inherent in machine learning of such regulation bring about the concern that the ‘rule of law’ might be exchanged for the ‘rule of technology’ – accompanied by *Kafkaesque*, *Huxleyan* and *Orwellian* discourses of dystopia.⁵⁰

4.1. Challenge to law as a normative enterprise

Rules, principles, standards and in general ‘norms’ provide uniformity, predictability, and social coordination for they inform individuals about their way of conduct, and explain the legal course of events in situations addressed by the Law. Law, hence, is a normative enterprise where the legislator consciously creates legal effects (institutional facts) that obtain when certain conditions are met.⁵¹

Any regulator will weigh various interests and decide what the norm should be in a particular constellation of facts. The norm is usually written down allowing the regulatees to take note of it and act accordingly. Regulatees are supposed to adhere to the norms and if they transgress the norm, face the consequences. However, normativity does not stop here, otherwise enforcing the norms through technology would potentially fully realise the ideal sketched by the law. Statutory norms represent the solidification of a political debate at a particular moment, taking into account only the foreseeable facts, interests and effects. Changing knowledge, opinions, interests etc, may require reopening the debate, and hence contestation of norms is an essential mechanism so that law and society can mutually evolve. Courts will decide how to cope with new arguments and new situations, and how to ensure that their verdict is enforceable and comprises law.

As explained above, there is some implicit normativity in every decision. Any decision-making system has a normative basis which may be seen as a totality of the decisional criteria, assumptions, and legitimations embedded in the system, specifying its behaviour.⁵² However, techno-regulatory settings based on data-driven correlations and inferences pose a challenge to law as a normative enterprise in that there are no clear enacted norms in the

⁴⁹This trilogy has been briefly visited in Ugo Pagallo and others, ‘New technologies and law: global insights on the legal impacts of technology, law as meta-technology and techno regulation’ New-Technologies-and-Law-Research-Group-Paper, 4th LSGL Academic Conference, Mexico 2017.

⁵⁰Roger Brownsword, ‘So What Does the World Need Now? Reflections on Regulating Technologies’ in R Brownsword and K Yeung (eds), *Regulating Technologies* (Hart, 2008) 23–48. For more on the implications of ML that may disrupt the concept of the rule of law, see Mireille Hildebrandt, ‘Law As Computation in the Era of Artificial Legal Intelligence. Speaking Law to the Power of Statistics’ *University of Toronto Law Journal* Volume 68 Issue supplement 1, January 2018, 12-35). <https://ssrn.com/abstract=2983045>.

⁵¹Brian Z Tamanaha, *A Realistic Theory of Law* (Cambridge University Press, 2017) 121. Also, see Dick W. P. Reuter, *Institutional Legal Facts: Legal Powers and their Effects* (Springer-Science+Business Media, 1993) 205-207.

⁵²MJ de Vries, SO Hansson, and AWM Meijers (eds), *Norms in Technology* (Springer Netherlands, 2013).

conventional sense anymore to provide a mapping between the facts and the legal effects.⁵³

In data-driven ADM, decision rules are (partially) *dynamic*. The norms imposed by these systems are not stable, but rather they are the objects of persistent and on-going reconfiguration.⁵⁴ The decisional rule itself emerges (autonomously) from the (dynamic) data used for training the system.⁵⁵ What is regarded to be the ‘norm’ is no longer predetermined, but constantly adjusted and opaque (normative opacity).⁵⁶ As inferential statistics and/or machine learning techniques produce probable yet uncertain knowledge, when statistics instead of reason *de facto* enter into the realm of norm setting, law loses its normative basis – at least to the extent that we associate normativity with human action.

A further type of normative opacity is due to the difficulties in discerning the *intention of the rule-maker*. In a data driven setting, the programmer sets the boundaries for learning, but as we have seen extraneous factors may find their way into the decisional rules. The normative impact of the ADM therefore is not solely determined by (legislative) intent. The affected individual cannot discern which part of the normativity (as could be inferred from the output) is intentional and which part is merely spin-off in the form unforeseen or secondary effects. Accordingly, the outcome in a data-driven setting may not be regarded as fully reflecting the intent of the competent body to enact rules.

Added to this is the *computational complexity* of data-driven systems.⁵⁷ Algorithms are unintelligible in the sense that the recipient of the output (eg a classification decision) rarely has any concrete idea of how or why a particular classification has been made (even if it is clear what the input was). The self-adjusting and adaptive capacity of data-driven systems renders them

⁵³As well, the specified variables could be the result of still other forces to which we should pay attention: a statistical model might gain accuracy by including the race, sex, age, and income of the parties, lawyers, and judges participating in a case without revealing precisely why or how these attributes influence decision-making. Useful variables will not necessarily map out decision dynamics’. Adam Samaha, ‘Judicial Transparency in an Age of Prediction’ (University of Chicago Public Law & Legal Theory Working Paper No. 216, 2008) 9.

⁵⁴See Brent Daniel Mittelstadt and others, ‘The ethics of algorithms: Mapping the debate’ (2016) 3 *Big Data & Society* (<https://doi.org/10.1177/2053951716679679>).

⁵⁵Massimo Buscema and William J Tastle (eds), *Intelligent Data Mining in Law Enforcement Analytics – New Neural Networks Applied to Real Problems* (Springer Netherlands, 2013) 14.

⁵⁶Massimo Buscema and William J Tastle (eds), *Intelligent Data Mining in Law Enforcement Analytics – New Neural Networks Applied to Real Problems* (Springer Netherlands, 2013) 14.

⁵⁷In contrast to human-made rules, these rules for decisionmaking are induced from historical examples – they are, quite literally, rules learned by example. Joshua A Kroll and others, ‘Accountable Algorithms’ (2017) 165 *University of Pennsylvania Law Review* 633, 679. Also see Matthias Leese, ‘The new profiling: Algorithms, black boxes, and the failure of anti-discriminatory safeguards in the European Union’ (2014) 45(5) *Security Dialogue* 501.

⁵⁷Anton Vedder and Laurens Naudts, ‘Accountability for the Use of Algorithms in a Big Data Environment’ (2017) 31 *International Review of Law, Computer & Technology* 206.

intractable and unintelligible to human cognition.⁵⁸ Opacity in machine learning algorithms is a product of the high-dimensionality of data, complex code and constantly reconfigured logic of the decision-making.

4.2. Challenge to law as a causative enterprise

Legal regulation is normative. Legal effects are not a matter of correlation between certain facts and effects, but of (legal) causation, or rather the law creates (constitutes) legal effects. The standard-setter determines which conditions lead to which legal effects. Data-driven ADM systems interfere with this mechanism due to their reliance on correlation.

Data analytics employ quantitative methods and statistical testing to process data resources to identify reliable patterns, trends, and associations among variables that describe and/or anticipate a particular process.⁵⁹ As a novel method of empirical inquiry, instead of starting with a question, Big Data reverses this process by first running the algorithms to look for patterns, and then retrospectively constructing hypotheses.⁶⁰ The seeming strength and comprehensiveness of this methodology relies on the magnitude of the datasets providing an oligoptic⁶¹ view of full resolution – the belief that ‘with enough data, the numbers speak for themselves’.⁶²

There are some evident restrictions and limitations of the methodology of extracting knowledge out of patterns and correlations identified in large datasets. First, in large enough datasets, even if data is selected arbitrarily, certain patterns will occur when analysis extends long enough. With so many possible dimensions, it becomes incredibly likely that some constructed type correlates with the outcome.⁶³

Some correlations are straightforward; almost axiomatic easy observations – for example, demand for flu medicine increases in winter, and more traffic accidents take place during rain. And some may be more subtle and sinister

⁵⁸Jenna Burrell, ‘How the machine “thinks”: Understanding opacity in machine learning algorithms’ (2016) *Big Data & Society*, 1–12; Antoinette Rouvroy, ‘The end(s) of critique: data-behaviourism vs. due-process’; Valeria Ferraris and others Working Paper ‘Defining Profiling’ (2013) https://www.academia.edu/5398935/Defining_Profiling; Ronald Leenes and Paul de Hert (eds), *Reforming European Data Protection Law* (Springer Netherlands, 2015); Nicholas Diakopoulos ‘Algorithmic Accountability: Reporting On The Investigation of Black Boxes’ (Columbia University, 2014): <https://academiccommons.columbia.edu/doi/10.7916/D8ZK5TW2>; Jatinder Singh, Ian Walden, Jon Crowcroft, and Jean Bacon, ‘Responsibility & Machine Learning: Part of a Process’, (October 27, 2016): https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2860048.

⁵⁹Stephan Kudyba *Big Data, Mining, and Analytics* (CRC Press, 2014) 29.

⁶⁰Mattioli (n 19); Chris Anderson, ‘The End of Theory: The Data Deluge Makes the Scientific Method Obsolete’, *Wired* (23 June 2008), http://archive.wired.com/science/discoveries/magazine/16-07/pb_theory.

⁶¹Rob Kitchin, ‘Big Data, new epistemologies and paradigm shifts’, *Big Data & Society*, April–June 2014, 1–12, 4.

⁶²Anderson (n 60).

⁶³Note that it is exactly the size of the data that allows our result: the more data, the more arbitrary, meaningless and useless (for future action) correlations will be found in them’. Cristian S Calude and Giuseppe Longo, ‘The Deluge of Spurious Correlations in Big Data’ (2017) 22 *Foundations of Science* 595. Also, see Scott E Page, *The Difference* (Princeton University Press, 2007) 85

like overweight persons make more spelling mistakes, while some are simply valuable such as the knowledge that a US citizen is more likely to register to vote after being informed that a close friend has registered. However, a correlation does not necessarily amount to causation⁶⁴ – for it does not inform us about the nature of the discovered relation. The correlation between independent and dependent variables in the analysis may be spurious. There may not be a causal relation between diapers and beer, though it may be equally plausible that people buying diapers have kids and therefore they consume beer at home, rather than going out with friends. In such cases, although the supposed cause and effect are related, in fact they may be both dependent on a third factor.

The meaning constructed through repeated observations over time and/or space does not necessarily explain but may undeniably rationalise what otherwise would be regarded as coincidental or unpredictable.⁶⁵ The basic premise behind data analytics is that the observation of correlations along the chosen parameters would extend into future events. However, a correlation may be a weak epistemological basis for prediction and thus, the so-called ‘truth’ offered by Big Data may turn out to be nothing more than a discursive self-intoxication.⁶⁶

Without doubt, certain correlations are useful observations for their practical relevance. However, as the data itself is not capable of justifying the assumptions and the perspective underlying a certain inference, correlations have no causative explanatory link unless narrated through a theory and implemented as a model based on that theory. Even though patterns are detected by algorithms, the input (data), algorithms to be used, and many other design choices make data analytics a model-building exercise. Therefore correlations are not ‘just discovered’, but also manufactured. This unfolds the further epistemological problem that causality in data-driven practices is a question of model-building which is itself a value-laden theorisation.⁶⁷ Thus, every predictive model inevitably discards certain part of the information about the world around us, and by doing so, it enables us to reach a digitised representation of the problem space which can be manipulated by means of algorithms.⁶⁸ In order to assess causal value, we need to know the range of alternatives from which a certain interpretation is derived, together with the principles and factors which generate that range of options.

⁶⁴Mayer-Schönberger and Cukier (n 18), ch.1.

⁶⁵A Jacobs, ‘The Pathologies of Big Data’ (2009) 52 *Communications of the ACM* 36.

⁶⁶Grégoire Chamayou, *A Theory of the Drone* (The New Press, 2015).

⁶⁷Stavros Ioannidis and Stathis Psillos ‘Mechanisms, Counterfactuals, and Laws’ in Stuart Glennan and Phyllis Illari (eds), *The Routledge Handbook of Mechanisms and Mechanical Philosophy* (Routledge, 2018). Also see Loise Amoore, *The Politics of Possibility* (Duke University Press Books, 2013) 44.

⁶⁸David M Berry, *The Philosophy of Software – Code and Mediation in the Digital Age* (Palgrave Macmillan, 2011).

An epistemology establishing causation between a multitude of data points through aggregation and recursive data analysis – insights of which may not be understood through direct human cognition – signifies the demise of law as a causative enterprise. Such a break of the causation chain is also a serious blow to human autonomy because individuals could no longer contest the result through rational argumentation. The collapse of the causative link may also be seen as a big leap towards dehumanisation of the social, economic, and political texture of our lives.

4.3. Demise of law as a moral enterprise

Data-driven models implementing rules or legal frameworks impair the rule of law by undermining the moral basis of the legal system on many fronts. First, the arguments within this context primarily relate to the notions of human autonomy and dignity as the higher principles of European legal and political order since the Enlightenment. Where technology is used to steer human conduct with a view to ensure compliance or for the implementation of certain norms, not only the normative character of law suffers from erosion, but also *human autonomy* and the moral grounds that the very norms are predicated upon. Especially where an *ex-ante* regulatory approach is taken – leaving no room for breach, or choice as to the way of compliance – our thinking of law departs from ‘should/should not’ to ‘can/cannot’, meaning that what is not legal cannot be done either.⁶⁹ Hence, techno-regulation can take away the freedom to deviate from the embedded norm in various ways.⁷⁰ Compare, for instance, the tourniquets found at different train and metro systems around the world. In some cases the barrier is man-high, in others one can easily climb/jump over them. In the first case, transgressing the norm is impossible, in the second the choice between morality and deviance is present.⁷¹ The difference may seem trivial, but taking away the personal choice by rendering certain behaviour impossible may lead to weakening of self-controls and may have a de-moralising effect.⁷²

Such erosion of human autonomy is aggravated in the case of data-driven DM models where the norms are not stable, but rather subject to persistent and on-going change and reconfiguration – making a moral anchoring less possible. This malleable and ‘fluid’ nature of data-driven systems make them particularly attractive as a regulatory tool, but very unattractive from

⁶⁹While ex-post methodologies discourage non-compliance or improve the chances of detection, without eliminating individual choice, the ex-ante approach overrides the individual as an intentional agent and automatically imposes the desired state or pre-empts certain behavior. See Kerr and Earle (n 30).

⁷⁰Leenes, ‘Framing Techno-Regulation’ (n 11); K Yeung, ‘Can we Employ Design-Based Regulation While Avoiding Brave New World?’ (2011) 3 *Law, Innovation and Technology* 1, 2.

⁷¹K Yeung, ‘Towards an Understanding of Regulation by Design’, in R Brownsword and K Yeung (eds) (n 50) 98.

⁷²DJ Smith, ‘Changing Situations and Changing People’, in A von Hirsch, D Garland and A Wakefield (eds), *Ethical and Social Perspectives on Situational Crime Prevention* (Hart, 2000).

the perspective of agent morality – eliminating the opportunities to act in a moral way by one's own will and thus undermining the conditions required for a flourishing moral community.⁷³ As explained above, although data-driven approach may cure the giddiness of rule-based systems to ensure 'efficient' compliance and execution, such positive gains are achieved at the expense of individual autonomy and agent morality. The adaptive and pre-emptive capacity of data-driven systems deprives individuals of the ability to reason with the rules.

Second, the application of Data Science techniques in the legal domain has been described as an important factor that may change how the legal services operate as well as the way the judiciary functions.⁷⁴ The core idea here is that data-driven legal analytics trained on data extracted from 'legal sources' such as case law and even doctrinal research will allow the construction of systems that will predict legal consequences with high precision—rendering the process of adjudication almost idle. Some even believe that a 'legal singularity' is near because the '... accumulation of massively more data and dramatically improved methods of inference make legal uncertainty obsolete.'⁷⁵ Whatever one may think of the feasibility of this, it may be the case that application of data analytics on the existing case law may produce a model that is able to accurately predict the outcome of every case that falls within the boundaries of the training set.⁷⁶ Indeed, the performance of systems trained on a set of cases may be good in the sense of accurately predicting the outcome of a case relative to its body of knowledge (the training set).⁷⁷ The outcomes of cases not covered by the training set are speculative and it is unknown whether these judgments are 'legally correct'.⁷⁸ In other words, the model

⁷³R Brownsword, 'Code, Control, and Choice: Why East is East and West is West' (2005) 25 *Legal Studies* 1, 17.

⁷⁴See, for instance, Richard and Daniel Susskind, *The Future of the Professions* (Oxford University Press, 2015); Daniel Martin Katz, 'Quantitative Legal Prediction – or – How I Learned to Stop Worrying and Start Preparing for the Data Driven Future of the Legal Services Industry' (2013) 62 *Emory Law Journal* 909.

⁷⁵Alarie Benjamin, 'The Path of the Law: Toward Legal Singularity' (May 27, 2016). <https://ssrn.com/abstract=2767835>.

⁷⁶This is a fundamental problem in AI and Law, known as the frame problem. Within the boundaries of the knowledge of the system, its performance may be good, but the system will not be able to handle cases outside these boundaries, nor will it generally be able to detect that a case actually falls outside its frame of knowledge/reference. It operates on a closed world assumption. Law, however, is a dynamic open system, engaging potentially with any case outside the system's perimeters. See Leenes (n 26).

⁷⁷In other words, these models do not really predict, but rather describe a historical data set, see Hildebrandt (n 6) 7.

⁷⁸The system can thus handle 'clear cases' as they are called in legal theory (see Dworkin), not 'hard cases', which can be taken to mean here cases that fall outside the frame of the system, or cases that are made to fall outside the frame by contestation. Nor does it notice a hard case has been presented to it. As a result of contestation, any case, also seemingly clear cases (or cases that are treated as clear by the system), may be turned into hard ones, for which the system may produce the wrong result. Moreover, even a perfect system (the magical algorithm, the point of legal singularity) will have diminishing returns, as the confidence of the system will be impaired by the decreased number of new cases to observe due to decreased need for adjudication. However, if seen from the perspective of cybernetics, this positive feedback may be offset in that the system's loss of reliability in time will result in more

can retrospectively predict the outcome of legal disputes only within a very limited understanding of what the law is about. As this may seem unproblematic and even laudable for helping the under-privileged access legal advice or facilitating the extra judicial settlement of disputes, Hildebrandt and others have rightly pointed out:⁷⁹

[...] law must be understood as a coherent web of speech acts that inform the consequences of our actions, itself informed by the triple tenets of legal certainty, justice and instrumentality that hold together jurisdiction (the force of law), community (even if between strangers) and instrumentality (the policy objectives of the democratic legislator).

The magical algorithm may render the law fully predictable, but it will still lack the necessary transparency and moral accountability in the sense of being open to scrutiny, and consequently compliant with the rule of law.⁸⁰ For being an affront to man's dignity as a responsible agent, replacing adjudication processes with predictable outcomes is a significant impairment to the rule of law for it undermines the moral premises of the legal system.

'Mathematical simulation of legal judgement' should not be mistaken for the judgment itself.⁸¹ Where decisions are not contestable through argumentation, there exists no authority to morally defend and justify the decision. Even if we knew that the analytics provide the best possible solution, and accurately predict the outcome of every possible dispute in advance, we would still need to render such decision intelligible so that it is transparent enough to be contested. Although such magical algorithm appears to relieve us from the burden of arguing cases before the courts, this does not in fact suppress the need for argumentation as a moral justification process. Delivery of an explanation to substantiate any decision is crucial in obtaining the necessary acceptance and endorsement from the individuals who are subject to the system. Adjudication not only provides redress but also has a connotation of morality through explanations that render the outcome normatively acceptable. The idea of predictive judgment, which eliminates the need for adjudicatory process, discards this moral signalling function of law.

5. Conclusion: conflicts to paradoxes

The pervasive employment of data-driven systems is indicative of our current and future dependence on technologies incorporating, articulating and

disputes being taken to court – eventually pushing the system back to perfection with the introduction of fresh data. Accordingly, instead of replacing the judiciary, predictive analytics may be used as a tool to monitor and audit actual court decisions.

⁷⁹Hildebrandt (n 6).

⁸⁰Samaha (n 53).

⁸¹Hildebrandt (n 6).

amplifying computational and calculative rationalities – linking ends to means in novel and humanly unintelligible ways.

Counting, calculating, accounting and eventually computing – a hectic obsession of modern humans – now has reached the point where we turn blind to almost anything that falls beyond or outside of our measuring capacity.⁸² The social complexity we live in dictates a paradigm where knowledge is limited without measurement.⁸³ This current prevailing understanding of data analytics and technology is rooted in the political philosophy of modern societies which is predicated upon a distinction between *politics* and *science*, according to which, while the former is supposedly based on values, the latter seeks for “objective truth”.⁸⁴

The problem with the emerging data-driven epistemology is that the kind of *knowing* it suggests is not always what we aim for or desire if we want to maintain the rule of law, but simply what technology allows us. Or as David Berry put it: ‘subtractive methods of understanding reality (*episteme*) produce new knowledges and methods for the control of reality (*techné*)’.⁸⁵

Data-driven processes increasingly re-embody norms within a form of an instrumentalized rationality. Data-driven instrumental reason converts each dilemma, conflict or antagonism, however material and fundamental, into a mere paradox which could be counteracted by the application of logic – substituting interests with the requirements of the technique and the normativity of law with the performativity of the algorithm. Big data constrains the possibilities for political and moral choices by reducing governance to a technical process of adaptation, and law to a process of optimisation – rendering politics a mere question of “better-doing”.⁸⁶

If the rule of law is taken as a meta-principle which primarily presupposes an autonomous subject who could effectively reason against the norms and introduce a novel interpretation,⁸⁷ the type of law that the data-driven paradigm implements, leaves no room for effective contestation – but only rationalised logical and probabilistic reasoning. This results in an all or nothing approach which hardly complies with the principles of proportionality, subject autonomy, expediency and certainty.⁸⁸ At some point, the binary

⁸²Frank George, *Machine Takeover, The Growing Threat to Human Freedom in a Computer Controlled Society* (Pergamon Press, 1977) 6.

⁸³Krenn (n 29); John Zerzan, *Why hope?: the stand against civilization* (Feral House, 2015); John M Henshaw, *Does Measurement Measure Up? How Numbers Reveal and Conceal the Truth* (The Johns Hopkins University Press, 2006).

⁸⁴Feenberg (n 39). Also, see Max Horkheimer, *Eclipse of Reason* (Oxford University Press, 1947, Continuum Publishing 1974, 2004).

⁸⁵David M Berry, *The Philosophy of Software Code and Mediation in the Digital Age* (Palgrave Macmillan, 2011) 15.

⁸⁶D Chandler, ‘A World without Causation: Big Data and the Coming of Age of Posthumanism’ (2015) 3 *Millennium: Journal of International Studies* 1.

⁸⁷Mireille Hildebrandt and others, ‘Introduction’ *Digital Enlightenment Yearbook 2013* (IOS Press, 2013).

⁸⁸TJ McIntyre and Colin Scott, ‘Internet Filtering: Rhetoric, Legitimacy, Accountability and Responsibility’, in Brownsword and Yeung (n 50) 109.

nature of Turing computation and its logical consistency eliminates any discretionary power as a capacity of the legal system to import extraneous knowledge to produce answers to the ‘hard cases’.

As the consequences of such formalisation of reason, our aims and values like justice, equality, happiness, solidarity and tolerance, which have been inherent in or sanctioned by reason since the Enlightenment, lose their intellectual ground. Although such values exist in the constitutions of the sovereign states, they lack any confirmation by reason or agency to link them to an objective reality.

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