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The Pixelated Person: Humanity in the Grip of Algorithmic Personalisation

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1.1 INTRODUCTION

By far the most fascinating and profitable subject of predictive algorithms is the human actor. The capacity to predict human preferences, responses and behaviours offers endless possibilities for science, commerce, politics and regulation, and promises convenience and efficiency that further private and public interests in equal measure. There is nothing inherently new about the attempt to predict buying choices, political leanings and likely votes of individuals and groups, the probable effectiveness of medical treatments, likely defaults on loans, the chance of fraudulent insurance claims or of reoffending. Yet, the capacity to 'know' the individual and the group, and to predict their constitution and behaviour has witnessed a sudden upturn of unprecedented scale. The rise of network society and smart technology is generating endless trails of personal data, finely pixelated digital footprints, that are aggregated into big data sets – that involve large collections (volume) of real-time (velocity), diverse and relational personal data (variety)[1] – about virtually all aspects of human life from shopping, food and entertainment preferences, friendship networks, romantic attachments, social activities, health concerns, physical movements, driving behaviour or sporting activities, to biometric data, such as voice, face, gait or keystroke, or physiological data on heart rate, blood pressure or sleeping patterns. These data sets, when mined by algorithms, can reveal significant patterns and correlations and, ultimately, produce knowledge about the group (e.g. behavioural trends, economic activity, delinquency, spread of disease, political trends, etc.[2]) *and* about the individual (e.g. educational level, social status, political leaning, sexual orientation, emotional states and psychological vulnerabilities as well as predilections for activities and movements). This knowledge then lies at the disposal of the private sector and government to be used for a wide range of purposes, implemented through 'personalised' services, treatments and regulation – some beneficial, some harmful, but mostly a mixture of both.

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For example, only a few Facebook 'likes' are needed to reveal correlations with personal attributes, such as sexual orientation, ethnicity, religious and political views, personality traits, intelligence, happiness, use of addictive substances, parental separation, age and gender.[3] These granular insights into the individual or micro-groups can be, and are, used to select and deselect content and advertisement to match their profile. Such 'personalisation' serves as essential information management (in response to the overwhelming amount of information available), and promotes efficiency (by saving users' time in searching through masses of content, and businesses the expense of serving adverts to uninterested users). For many, personalisation offers the customisation and optimisation previously only available to the elite, e.g. the personal advisor or trainer, whilst the great masses had to be content with mass production. Mass-personalisation or individualised consumption at scale is now possible at least in the service industry.[4] Yet, the very same practices that appear so beneficial show their exploitative dimension when used to extract extra value from the consumer as, for example, when an inferred desperate search for a loan is translated into an offering of credit with a 'personalised' higher interest rate that reflects the urgency of the search. Equally, the manipulative aspects of personalisation shine through in the practice of micro-targeting political adverts to profiled users, and undecided voters, in the lead up to elections or referendums, as revealed in the Cambridge Analytica scandal.[5] Although the scandal centred on the deceptive collection of data and the absence of user consent to such collection and use, consent seems to only marginally address the manipulative inflection of political (and other) micro-targeting. Even where targeting is consensual, the 'opted-in' lack of choice and consequential lack of exposure to alternative narratives still seem problematic. By the same token, if a patient's personal medical history is supplemented by a genetic profile from an ancestry service, like 23andMe, and life-style data from a Fitbit watch in order to decide on the most effective made-to-measure medical treatment,[6] this process seems in the patient's interest (most effective treatment) and in the public interest (efficient allocation of scarce resources). Yet, the same practice becomes more suspect when used to limit otherwise available treatment options or deny treatment altogether, on the basis of unfavourable DNA or life-style profiles. Finally, the possibility of predictive policing through micro-segmentation of populations promises to employ scarce police resources more efficiently by concentrating on likely serious delinquents and thus to pre-empt crime and disorder more effectively. Yet, he who seeks finds: the distorting impacts of such targeted practices have been well documented, and one of their concomitant side effects is that some sections of the population are granted leeway from which others do not benefit, often along historic racial and ethnic lines of division.[7]

Whether beneficial or detrimental, what these scenarios have in common is the data-driven profiling of consumers or citizens to deliver a customised or personalised service, advert or legal response. Personal data in conjunction with big data is interpreted by algorithms to create a picture of who someone *is* based on who they *were* – their past preferences, activities, networks and behaviours – in order to make a future-oriented prediction of what they might like (i.e. which film), what might persuade them (i.e. which ad) and how they might act (i.e. commit a crime or succeed in a job). A key problematic of profiling and customisation practices lies in their very virtue: the pre-selection and pre-emption of individual choices by those with access to big data sets and profiling technology. Thaler and Sunstein have called them 'choice architects' in the context of 'nudging'.[8] The pre-management of individual choices by these architects is rendered at times more benign by the triviality of the personalised service, e.g. a recommended book, film or song; or by the perspective of those upon whom personalisation bestows a benefit based on their 'good' profiles, e.g., the healthy patient, the unlikely delinquent, the creditworthy or price-sensitive consumer.[9] The core of the problem, however, remains the same and lies, first, in taking the human agent out of the loop of participating and directing her individual and collective life through making active choices,[10] in potentially two capacities: one, the algorithm replaces the traditional human decision-maker (e.g. the judge or the editor or the business person) and, two, those decisions then also pre-empt the choices of the profilee (e.g. the defendant or consumer). Choices are made for her, or at least the framework is created within which she can make her choices. The *second* problematic underlying personalisation practices is that big data analytics is generated by autonomous technology whose complex processes, optimised through feedback loops and machine learning capabilities, often place it beyond human comprehension, and thus *prima* facie also outside human oversight and contestation.

This collection of essays engages with these problematics in various social domains and academic fields of inquiry, and brings together scholars from different walks of law (data protection and privacy law, criminal, medical, and contract law as well as constitutional theory) and other social sciences, such as political theory, human geography, criminology, behavioural economics and philosophy, to interrogate this new powerful phenomenon that is sweeping across economic, political, social and legal domains, and dramatically reconfigures our social structures. What is striking about the contributions is that, despite the different contexts and perspectives, persistent themes emerge. On a practice-focused level, data-driven profiling and its myriad uses raise questions about *substance* (e.g. what is the accuracy of the profile and the legitimacy of using probabilistic predictions in favour of, or against, an individual, particularly in light of the possibility of mistakes or discrimination; what are the wider unintended consequences of profiling on private and public or collective interests) and about *process* (e.g. what oversight, if any, is exercised over the autonomous decision-making technology?; can informed consent ensure the empowerment of users in their profile creation and, more generally, to what extent can and should individuals be able to resist and challenge the collection of their data, its aggregation and use?; and how does it impact on avenues for collective resistance?).

On a theoretical level, there are also clusters of ideas that cut across subject-matters and disciplines, and flock around two themes. The first focuses on the foundational premise of predictive technology which is that future actions can (and should) be inferred from past behaviour or from the behaviour of like actors – a premise which is at odds with ideas of moral agency and free will. Yet, agency lies at the heart of our social orders and underpins the *homo economicus*, the self-determining citizen, and the moral actor who can only be held responsible for their actions on the basis of the freedom to act otherwise. Moral agency is also closely related to our conceptions of identity and personhood, and the open-ended evolving nature of human individuality. These conceptions are profoundly challenged by the creation of the *pixelated human* – a digitally constructed, two-dimensional, instrumentalised, commodified representation of individuality – and yet, this entity is frequently treated as the authentic self. Furthermore, under this deterministic view of human behaviour, normative questions are reduced to, or disguised behind, empirical observations about individual and group histories. This essentialist approach has the effect of continuously reasserting the status quo, and thereby consolidating and exacerbating it, including existing inequalities, structural disadvantages or political world views, and concomitantly reducing the room for individual or collective betterment.

The second cluster of ideas places the granularly profiled user from whom value can be extracted (generally in the name of efficiency) within a sharpened capitalist economic order. Shoshana Zuboff argued that the new data practices have given rise to surveillance capitalism: 'surveillance capitalists discovered that the most predictive behavioral data come from intervening in the state of play in order to nudge, coax, tune and herd behavior toward profitable outcomes.'[11] This perspective helps to frame the heightened user-pay model that various personalisation practices (e.g. personalised health care, credit or insurance products) implement as instantiations of liberal ideas of individualist fairness or just desert in opposition to notions of communal solidarity or distributive justice.[12] The free market lens also helps to explain why consent and personal autonomy should so systematically underwrite profiling practices, regardless of the facts that users exercise that autonomy within vastly asymmetrical power relations; that it legitimises value extraction as opposed to offering protection; and that invariably more is at stake than individual private interests. Equally the commodification of personal data is only intelligible against market logic. When consumers can sell their personal data in return for 'free' services, and corporations can buy and ring-fence this vast resource, the potential of these data sets as a (global) public good to be used for the benefit of all becomes much more circumscribed.[13] At the same time, the micro-segmentation of communities through personalisation practices, legitimised by individual consent, fragments political communities and distorts democratic processes, with the compounding effect of weakening a key mechanism for holding corporate and governmental actors to account, and for restraining the very processes that undermine those democratic processes.[14] In short, profiling and personalisation practices are deeply inscribed with capitalist market values – from their initial conception and rationalisation to their implementation within economic, social and political spheres and their continuing legitimation.

If there is one theme that carries through the whole collection, it is that this newly emerging and highly disruptive phenomenon has continuities with previous practices, concepts and ideologies, through which it may be analysed and critiqued. It is also only against these previously established understandings and processes that we may recognise how it presents a paradigmatic shift that really deserves our assiduous attention before it has pervasively and conclusively reshaped our social orders in its own image. This introductory chapter provides reflections on two distinct intellectual hinterlands to the more specific themes and applications of data-driven personalisation practices in this collection. First, it situates these discussions against a general framework of profiling and defends data-driven individual and group profiling against some critiques of stereotyping, on the basis that our cognition of the external environment is necessarily reliant on relevant abstractions or non-universal generalisations. The second set of reflections centres around the philosophical tradition of empiricism as a basis of knowledge or truth production, and uses this tradition to critique data-driven profiling and personalisation practices in its numerous manifestations. The final part of the chapter summarises the chapters in this volume and their individual contribution to the overall narrative.

1.2 INDIVIDUAL AND GROUP PROFILING AND THE VIRTUES OF STEREOTYPING

1.2.1 *The Interdependence of Individual and Group Profiling*

An initial controversy surrounding algorithmic profiling based on large sets of digital footprints is whether the individual or the group is its real target and the potential object of manipulative practices. Whilst the language of personalisation and customisation suggests the individual is the focal point, in some ways 'personalisation' is a misnomer, as individual profiling is always a form of classification whereby the individual is assessed against group attributes (more on that below) and then put in a micro-category for the purpose of delivering the 'personalised' response or service. Thus although the individual is the target of the customised message, service or treatment, the outcome is based on group features and multiplied across the micro-group. Furthermore, the fact that individual profiling is premised on analysing data sets about populations – mined for correlations and leading to the construction of groups in the process – has led some to conclude that *group* profiling is the critical new phenomenon that challenges existing legal modalities:

> The search for group privacy can be explained in part by the fact that with big data analyses, the particular and the individual is no longer central. In these types of

> processes, data is no longer gathered about one specific individual or a small group of people, but rather about large and undefined groups. Data is analysed on the basis of patterns and group profiles; the result is often used for general policies and applied on a large scale.[15]

This argument has some validity (given that privacy regimes envisage an individual victim, and harm to the group only derivatively), but the ability to micro-profile individuals is still at least as valuable to corporate and governmental actors as knowledge about the group, as borne out by the widespread emergence of personalisation practices. In any event, the individual-versus-group dichotomy may largely be misconceived because they reflexively interact with each other. Individual data feeds into population data sets and these sets produce, through correlations, knowledge about populations, that is patterns and groups within them (inductive), which in turn are instructive about the individual (deductive).

The close, yet varying, integration of individual and group profiles has been subject to some debate and conceptualised in the distinction between distributive and non-distributive group profiling.[16] For *distributive* profiles (universal generalisations) attributes of the group are 'actually and unconditionally manifested by all the members of that group'[17] and thus group membership also allows for definitive inferences about the attributes of its members.[18] Every member of university staff (the group) has an employment contract with the university and a salary (attributes). In contrast, *non-distributive* profiles (non-universal generalisations or stereotyping) refer to groups where a family resemblance unites members, but not every member shares every attribute.[19] Here 'a group is defined in terms of… *significant deviances from other groups*. They are based on comparisons of members of the group with each other and/or on comparisons of one particular group with other groups.'[20] The group boundaries in non-distributed profiles are inevitably fuzzy. Those with a high risk of cardiovascular disease (group) share a number of risk factors, for example, lifestyle, genes, age, weight, etc. (attributes),[21] but membership does not allow for definitive inferences about the particular attribute of a particular member. The non-universal generalisation that 'young men drive recklessly' does not allow for a definitive inference about the driving of any particular young man but, as argued below, mistakes on the individual level are often legitimated by the benefits of identifying (empirically sound) tendential truths.

Whilst non-distributive profiling explicitly compares one group *vis-à-vis* other groups, ultimately the distinctiveness of a distributive group profile (university staff) can also only be understood against other groups, that is what it is not (police or hospital staff, or university students). Indeed, the difference between these two types of profiling may in practice (and theory) not be that clear cut (i.e. is the whiteness of swans 'necessarily manifest' or non-essential?) and becomes largely a function of the profiler's knowledge, pre-conceptions and attendant construction of the group. This suggests that the certainty of (empirically based) distributive profiles may be illusory.[22] The two types of profiling may simply reflect different philosophical traditions: distributive profiles adopt a Platonic top-down perspective on a concept or class that assumes and finds a common essence underlying all its manifestations, whilst non-distributive profiling builds on Wittgenstein's bottom-up (and empiricist) notion of family resemblance whereby concepts or words just refer to clusters of similar or related phenomena:

> Consider for example the proceedings that we call 'games'. I mean board-games, card-games, ball-games, Olympic games and so on. What is common to them all? – Don't say: "There *must* be something common, or they would not be called 'games'" – but *look and see* whether there is anything common to all. – . . . [W]e see a complicated network of similarities overlapping and criss-crossing: sometimes overall similarities, sometimes similarities of detail..[23]

So arguably distributive and non-distributing group profiling does not refer to different types of groups, but rather to different ways of looking at the same group, or, more precisely, to different ways of *constructing* groups.

As non-distributive profiling can capture a wider range of relevant, albeit non-essential, attributes (as opposed to seeking a group's essence), it yields a much richer picture of groups and individuals, but also has blurry edges and is fallible in respect of making definitive inferences about its members.[24] This is significant for big-data individual profiling, or any form of statistical profiling: when individual profiles are inferred from comparison with the group (indirect profiling), it may be tempting to fill 'gaps' in an imperfect overlap with the missing group attributes. For example, in the policing context, a large aggregated criminal justice database with data on criminal activities mapped onto post codes, on criminal records and recidivism, social media activities and networks, education and employment histories of offenders, and personality traits may – based on strong correlations – predict for a particular offender a high risk of recidivism. The Harm Assessment Risk Tool, or the HART algorithm, used by Durham Constabulary makes such predictions based on 509 'votes' by the system.[25] A digital footprint on social media may, in the absence of explicit evidence, be analysed to 'reveal' the missing attribute of a single person's status, a left-wing political outlook or homosexuality. Based on the strength of the correlation, an unknown attribute may be 'highly likely' and in this respect fall somewhere between the distributive and non-distributive profiles – as neither necessarily manifest nor simply possible. However, the effect of the use of the predictive technology will often be such as to treat highly likely predictions as effectively established, along the lines of Plato's essentialism. Yet, there may be rights-based reasons, such as the presumption of innocence or the right to privacy, why a particular inferred attribute should be treated as non-essential and its absence presumed, as, for example, when sensitive data may be inferred from a range of non-sensitive data points. (Chapter 5)

1.2.2 The Virtues of Stereotyping

One persistent objection to individual profiling based on comparisons to group data, including big data profiling, is that the resultant stereotyping (or non-universal generalisations) leads to the 'deindividualisation of the person' which occurs when '[p]ersons are judged and treated more and more as members of a group (i.e. the reference group that makes up the data or information subject) rather than as individuals with their own characteristics and merits.'[26] This critique is directed at *indirect profiling* that draws inferences about the individual from group data (invariably through non-universal generalisations), as opposed to *direct profiling* that is ostensibly based on data only about the particular individual and therefore arguably more accurate.[27] The objection to the 'deindividualisation of the person' or stereotyping based on comparisons with the group is flawed for a number of reasons. First, the argument that direct profiling delivers *prima facie* more legitimate profiles as it is solely focused on the digital footprint of the single individual assumes that someone's past activities and preferences provide a valid yardstick for his future behaviour and preferences, and implicitly assumes that personhood is fixed in time. Such reasoning relies as much on stereotyping of the individual (and on denying agency) as indirect profiling, as it does not allow for the possibility of continual reinvention and development of individuality through repeated assertions of free choice. Indirect profiling has at least the virtue of squarely acknowledging that 'no man is an island' and that individuality is intimately tied up with social forces within which it develops and against which it may be understood. Still, *all* profiling used for predictive purposes is inherently irreconcilable with the notion of free will as underwriting moral and legal responsibility as well as autonomous participation in democratic processes.

Second, direct profiling is also necessarily comparative with the group, much like indirect profiling, and cannot but invoke the social dimension of human existence. Individuality can only be understood against an assumed 'normality' which contextualises individual divergence.[28] An individual's social media digital footprint is entirely meaningless by itself, in a social vacuum. It can only signal depression or creditworthiness or criminogenic tendencies against data sets, drawn from the group, that display the whole spectrums of psychological, financial or criminogenic states.[29] The interdependence of the individual and the group, the particular and the general, uniqueness and commonality, may best be illustrated with reference to DNA profiling as the biological equivalent to behavioural profiling:

> DNA fingerprinting (also called DNA profiling or forensic genetics) is a technique employed by forensic scientists to assist in the identification of individuals or samples by their respective DNA profiles. Although more than 99.1 per cent of the genome is the same throughout the human population, the remaining 0.9 per cent of human DNA shows variations between individuals.[30]

In parallel with the biological profile, where commonality far outweighs uniqueness, and individual genomic variations operate, and are identifiable, against genomic commonality, individual behavioural uniqueness can also *only* be conceptualised against the broad brush of collective humanity. The specific and the general are co-dependent. (See Chapter 5.)

Last, but not the least, even if direct and indirect profiling are, after all, not so fundamentally different from each other by being comparative and engaging in stereotyping, the crux of the problem may lie in stereotyping *per se*. The argument against stereotyping appears to have found legal recognition in antidiscrimination law: 'Stereotyping, or the imposition of assumptions about a group on an individual, has been central to antidiscrimination law because of the prominence of individual autonomy as a juridical value.'[31] This assertion, however, is misleading in its generality, considering that antidiscrimination law only addresses stereotyping based on a very limited range of factors, for example, race, gender or age. It does not outlaw stereotyping *per se*, nor could it. Human judgment and knowledge invariably, and necessarily, involves stereotyping – or non-universal generalisations – and this is neither irrational nor immoral, assuming it has a sound empirical basis *and* excepting certain historically disadvantaged groups, as protected by antidiscrimination law. Frederic Schauer in *Profiles, Probabilities, and Stereotypes* has argued for the ubiquity of stereotyping and its *prima facie* legitimacy:

> We operate actuarially when we choose airlines on the basis of their records for safety, on-time performance or not losing checked luggage. We operate actuarially when we associate personal characteristics such as a shaved head, a tattoo and black clothing with behavioral characteristics, such as racist beliefs and a propensity to violence, that the personal characteristics seem probabilistically but not inexorably to indicate... Still, once we see... that employers stereotype when they assume that certain characteristics (good grades from a prestigious university) will predict successful job performance, that police detectives focus on suspects by aggregating stereotypes, and that most of us stereotype in much of our daily lives, we cannot so easily dismiss the practice of stereotyping – or profiling – as necessarily morally wrong.[32]

In all these cases, stereotyping, or non-universal generalisation, is based on an acceptance of inaccurate results in particular cases (e.g. in a job, a particular student with poor grades might outperform the students with good grades; a plane from an airline with a good record may crash), but is still justifiable on the ground of efficiency. Shortcuts and proxies (e.g. the grade, the tattoo, the airline brand) reduce informational complexity and thereby facilitate decision-making that is faster and, if empirically sound, also tendentially correct, albeit not 100 per cent. In fact, as Schauer shows, such stereotyping often leads overall to fewer mistakes than a case-by-case approach where wide discretion and factual granularity and complexity introduce far more room for errors of judgement and inconsistencies.[33] In other words, from an efficiency perspective, empirically sound stereotyping allows *overall* for faster and better decisions. Having said that, the possibility of mistakes *is* problematic in serious contexts, such as criminal justice, which has traditionally been deeply individualistic and thus preoccupied with avoiding false positives.

Considering that the antithesis of stereotyping is a case-by-case or particularised approach, stereotyping is a form of rule-based decision-making: a proxy provides a simple instrumentalised yardstick against which individuals (or products or situations) are measured, and can be seen to be measured. So counterintuitively, stereotyping has the moral virtue, first, of facilitating – at least in principle – transparency and accountability, as judging by proxy creates simplicity (by removing informational noise) and makes it possible to understand how a judgment was reached. Given this transparency, the stereotyped individual is also often, not always, able to actively participate in his perception by others, for example, by working towards good grades or getting a tattoo. Stereotyping is then a two-way process whereby the individual deliberately sends relevant signals for the judgment of others, or contests the accuracy of the perceived stereotype in her particular case. Second, generalisation or stereotyping is also virtuous because applying a proxy equally to all, in disregard of individual differences, is aligned with the concept of formal equality, which in turn is fundamental to our understanding of fairness and justice. Resorting once more to Schauer, the value of formal equality lies in 'understanding our common situation and our common plight as one in which there are limits to how much difference our own personal individual situations ought to make. It is no accident that Justice wears a blindfold. And she wears a blindfold not because she needs to steel herself against her own biases, prejudices, and mistakes, but because it is central to one conception of justice that equal treatment for its own sake – treating unlikes alike – serves important functions.'[34] Thus stereotyping applies a social framing to individual treatment, stressing commonality over differences, and thereby reinforces community and affinity.

Outside the legal or social context, the systematic use of proxies to make non-universal generalisations about the external environment (e.g. brown bears = danger; koalas ≠ danger) produces knowledge that enables choices about alternative courses of action and is thus fundamental to evolutionary success. Mireille Hildebrandt observed that 'all living organisms, in order to survive, must continuously profile their environment to be able to adapt themselves and/or adapt the environment.'[35] Taking this perspective, profiling and stereotyping is an essential survival mechanism that consists of abstracting (life-critical) information from the environment in order to adapt to it, or vice versa. It is goal oriented and selective by focusing only on relevant features and by making generalisations that are tendentially true but not always – much like present day profiling by autonomous technology.

In short, whilst there may often be valid arguments about the empirical (un)soundness or other (il)legitimacy of a *particular* basis of stereotyping, in general, judging by proxy is not just intrinsic to the cognitive processing of external reality and fellow humanity, but also has solid moral foundations. Therefore, in so far as objections to direct and indirect profiling are centred on the intrinsic wrongfulness of stereotyping, they are based on a misunderstanding about its role in knowledge production and moral discourse. By the same token, big data-driven profiling and personalisation practices may be criticised for *undue* stereotyping, where the profiling is empirically unsound, or draws on proxies for groups that have suffered long-standing structural disadvantages. (Chapter 11) Furthermore, big data profiling does not facilitate stereotyping practices in which everyone engages equally, but is underwritten by power asymmetries which it consolidates and sharpens, to which the discussion will turn now.

1.3 KNOWLEDGE AND TRUTH PRODUCTION THROUGH AI – THE NEW AGE OF EMPIRICISM

1.3.1 *Blind Knowledge of Data-driven Profiling: Correlations, Not Causation*

Big data analytics, of which individual and group profiling is a prominent example, constitutes – in method, if not aim – the quintessential manifestation of the epistemological tradition of empiricism. For empiricists, in contradistinction to rationalists, the only reliable source of knowledge is information gathered through sense experience or observation. Knowledge follows experience rather than precedes it. For the early English philosopher of science and Enlightenment empiricist Francis Bacon, scientific knowledge had to be based on observations of nature and could only be produced through inductive reasoning – yet not without being guided by some form of hypothesis: 'the true method of experience, on the contrary, first lights the candle, and then by means of the candle shows the way'.[36] David Hume, writing more than a century later, was equally persuaded of the need for observation in matters of fact (as opposed to relations of ideas, i.e. mathematics or logic):

> In reality, all arguments from experience are founded on the similarity which we discover among natural objects, and by which we are induced to expect effects similar to those which we have found to follow from such objects. And though none but a fool or madman will ever pretend to dispute the authority of experience, or to reject that great guide of human life, it may surely be allowed a philosopher to have so much curiosity at least as to examine the principle of human nature, which gives this mighty authority to experience.[37]

As a philosopher, Hume was sceptical about inductive reasoning as a source of true knowledge. For him an observed 'constant conjunction' or correlation (i.e. the sun has risen in the past) does not give us an epistemic basis to *know with certainty* that the same will occur in the future (i.e. the sun will rise tomorrow) – even if observers generally jump to such conclusions and thereby imply an underlying scientific law about cause and effect, from which the future can *demonstratively* be known.

Hume's sceptical empiricism is uncannily enacted by big data analytics in general, and individual and group profiling in particular – even if in a distorted fashion. Big data analytics produces 'blind' knowledge, or knowledge of 'constant conjunctions' or correlations, and often stops at that. *Prima facie* it is the correlation, rather than an explanation for the correlation or true knowledge, that matters. Methodologically, big data analytics makes a hypothesis drawing on a theory – as the foundation for trial-and-error scientific method – far less important than it is for traditional scientific discovery. Knowledge discovery in databases occurs by searching for relevant correlations or patterns with the help of algorithms, and 'these algorithms can be supervised, that is they can start with a hypothesis that is tested on the data, or they can be unsupervised,… and just check for any patterns… [in line with a particular] mathematical function.'[38] Thus an unsupervised algorithm proceeds – without Bacon's candle – to search itself for structures (or groups) in the input data towards a desired output. Having said that, there is a hybrid methodology whereby initial data results are used to generate the hypothesis for further statistical testing on other (validation) data.[39] Second and overlapping, in *Big Data: A Revolution That Will Transform How We Live, Work, and Think*,[40] Viktor Mayer-Schönberger and Kenneth Cukier commented that the move from a small-data to a big-data world has unleashed the power of correlations. The abundance of data and sophisticated analytical tools allow for faster and cheaper identification of correlations on a much wider range of subjects – with or without *a posteriori* explanations about cause and effect. Indeed, attempts to explain correlations are, according to the authors, often 'caught in a web of competing causal hypotheses… [and] only make them cloudier. Correlations exist; we can show them mathematically. We can't easily do the same for causal links. So we would do well to hold off from trying to explain the reason behind the correlations: the *why* instead of the *what*.'[41] Thus they conclude, in a twisted nod to Hume, that '[c]ausality won't be discarded, but it is being knocked off its pedestal as the primary fountain of meaning.'[42] Similarly, Chris Anderson had previously – in 'The End of Theory: The Data Deluge makes the Scientific Method Obsolete'[43] – argued that the abundance of data displaces every theory of human behaviour, from linguistics to sociology or psychology, given that it no longer matters knowing 'why people do what they do[.] The point is they do it, and we can track and measure it with unprecedented fidelity. With enough data, the numbers speak for themselves.'[44] These commentators effectively dissolve Hume's intractable dilemma about the possibility of true knowledge (which Kant had already done rather effectively in 1781[45]) by asserting that such knowledge is now redundant.

This argument for the virtues of instrumentalised blind 'knowledge' of big data analytics (if it can be called knowledge) presents a full inversion of Enlightenment ideals of rationality and scientific discovery, even if the claim of a paradigmatic shift in science is to some extent exaggerated. Some theory invariably drives and follows the search for correlations.[46] Mireille Hildebrandt has shown how wider theoretical assumptions are necessarily embedded, even within unsupervised learning algorithms, in the constructions of a model of reality by translating external reality into data sets, and 'theory' is also implicated in reviewing the validity of found correlations.[47] Furthermore, data simply never speaks for itself: 'Making sense of data is always framed – data are examined through a particular lens that influences how they are interpreted.'[48] Still, whilst exaggerated, the core assertion about the new approach to discoveries stands, even if it over-promises results outside retail and marketing. (Chapter 15) Peter Coveney and others have argued – using precision or personalised medicine and human genomics projects as an example – that big data knowledge discoveries often fail beyond the big-yet-finite data sets on which they are trained precisely 'because they are not designed to model the structure characteristics of the underlying system.'[49] In the human behavioural domain, data sets may prove to be 'finite' in terms of being time-specific or valid only for certain sections of the population. From a scientific perspective, there is also the rather more principled objection about discarding the quest for real knowledge in favour of the new instrumentalised 'knowledge': 'In subjects where the level of theoretical understanding [i.e. physics and chemistry] is deep, it is deemed aberrant to ignore it all and resort to collecting data in a blind manner. Yet, this is precisely what is advocated in the less theoretically grounded disciplines of biology and medicine, let alone social sciences and economics.'[50] Notably, these latter disciplines provide the scientific backdrop within which individual and group profiling generally falls.

From an economic perspective, the blind 'knowledge' of big data analytics is wholly legitimated by efficiencies: if data-driven profiling generates revenue or saves scarce public resources, and effectively predicts (or moulds) choices, it matters not what the underlying reasons may be. On a more generic level, Andrew Feenberg has argued that *efficiency* and *control* are the inherent animating forces of 'technology' rather than values that offer an outside perspective on technology: 'To judge an action as more or less efficient is already to have determined it to be technical and therefore an appropriate object of such a judgment. Similarly, the concept of control implied in technique is "technical" and so not a distinguishing criterion.'[51] In other words, the very adoption of predictive algorithms in various social domains signals the entry of 'efficiency and control' as a dominant frame *vis-à-vis* alternative ways of engaging in the activity (e.g. research or understanding voters) and *vis-à-vis* alternative perspectives for evaluating the merit of the activity or outcome (e.g. 'pure' knowledge discovery, moral and political deliberation, human rights, equality, the rule of law or production of happiness). Feenberg's observation also helps to explain why 'efficiency' should loom so large as justification for predictive and profiling technology, whilst 'control' or potential abuses of control feature heavily in its critique.[52]

Given the 'natural' home of efficient technology in an economic conception of reality, it is perhaps not surprising that individual profiling and personalisation practices have been the most 'successful' in retail and marketing, that is, in terms of maximising efficiencies and control from a corporation's perspective (although not necessarily from other perspectives, e.g., democratic deliberation). Famously, Amazon's phenomenal rise was grounded in its recommender system that benefits from constant feedback loops for auto-correction, and can predict highly accurately the buying preferences of their customers and so helped to dramatically increase sales.[53] Such micro-targeting is now ubiquitously used by platforms, retailers and advertisers to order content and push products. Within the commercial realm, it is clear that the correlations themselves are valuable for the profilers, who would hold no further interest in the explanations behind the correlations.[54] If there were a correlation between a behavioural pattern on social media and excessive purchasing behaviour, it would be irrelevant to an online retailer for targeting adverts, that the common cause of the behavioural and purchasing patterns may be varying stages of depression. Being ignorant of the causes behind non-spurious correlations makes the extraction of economic value morally neutral, particularly as algorithmic value extraction generally draws on some weakness or susceptibility of the consumer. Empiricism's apparently neutral focus on facts or corrections, not framed by explanations, provides the toolkit for de-moralising economic activity. Big data analytics realises that ambition more fully and forcefully than any previous metric or actuarial practice, as it has the strongest claim yet about the self-generated emergence of insights from data sets without human intervention.[55]

This new 'empiricism on steroids'[56] or the pursuit of data-driven blind knowledge has been equally attractive to governments that likewise chase efficiencies for their governing economies. Predictive algorithmic tools used for policing or sentencing are designed to use public recourses in a more targeted fashion and thereby deliver 'better' (more efficient) results, as in turn assessed by metrics. In the civil domain, smart city projects are driven by the prospect of efficiency gains by measuring traffic and footfall to enable live-management of traffic, parking, services, utilities, waste, etc. (Chapter 12) The continuous profiling of human activity aimed at facilitating efficient city life also provides ample opportunities for embedding policing activities, for example, speeding on smart motorways or unauthorised smoking,[57] whilst, at the same time, insidiously nudging populations – with a low-level awareness of an ever-present intelligent environment – into self-disciplining (control). (Chapter 3) Much like in the commercial context, the new algorithmic empiricism offers the added bonus of disassociating government from sensitive decisions. For the impersonal bureaucracies of governments – long familiar with cost-benefit analysis, evidence-based practice and impact metrics – big data algorithmic decision-making holds the promise of removing further residues of:

> individual authority [that] is perceived or portrayed as inadequate, inefficient, partial, paternalistic, corrupt, or illegitimate. In these areas, fully formalized, automated decisions have become more and more attractive as effective and supposedly neutral or even democratic procedures, in particular if they implement an empirical component that can be presented as 'carrying' the actual decision. Responsibility can then be shifted to the data themselves.[58]

So the combination of 'self-generated' data and insights and automated decisions allows for standard normative evaluations to be shifted from political, legal or economic domains into the technical realm. Whilst the former require reasoning, judgment and communications that are necessarily contestable (Chapter 16), decisions made by technology appear to be incontestable and are, for that reason, as democratically problematic as tempting for bureaucracies. They appear incontestable not just because of the natural opacity of predictive analytics (recalling that unsupervised learning algorithms operate without a formal 'theory' within black boxes and are 'adaptive' to new data), but also because machine-generated decisions seem objective, neutral and rational, and not infested with human prejudice and fallibility. Notably, there is evidence that decisions based on experience and intuition are inferior to decisions based on simple rules implemented in weighted checklists, and the latter rival machine learning algorithms.[59] (Chapter 15) The justification for decisions by technology is thus arguably higher quality, but also, incidentally, it allows for responsibility to be shifted. Yet, 'the choice of a technical rather than a political or moral solution to a social problem is politically and morally significant,'[60] and neither technology itself nor its decisions are apolitical or amoral.[61]

1.3.2 *The 'truth' and 'accuracy' of Big Data Profiling*

A related set of questions that flow from the empiricism of data-driven profiling and predictive practices centre around issues of truth and accuracy in light of the apparent impartiality and objectivity of statistical analysis: facts do not lie, they speak for themselves; numbers can be trusted. Implicit truth or accuracy claims bolster the authoritativeness of predictive algorithms, resulting in their apparently superior fairness. These claims can be unpacked on multiple levels as has already been comprehensively in existing scholarship.[62] For the purposes of framing this collection, three brief reflections will suffice.

First, big data analytics, much like all statistical evaluation, is neither neutral nor objective. It inevitably embeds value judgments, and often perpetuates societal prejudices and biases. Just because unsupervised learning algorithms act ostensibly on their own does not mean their outcomes are free from biases. All algorithms are trained on data sets and replicate, in developing predictive models, the biases implicit in these sets, known *inter alia* as the 'black data' problem.[63] With traditional statistical modelling based on smaller and more structured data, it was possible to make conscious efforts to counteract biases against disadvantaged groups by deselecting obvious proxies of sensitive attributes (e.g. postcodes for race). Such editing is less feasible in respect of large sets of non-traditional, behavioural data, given that much apparently innocent data (e.g. cultural preferences or educational achievement) is correlated to sensitive attributes, as shown in research.[64] This means that big-data profiling based on innocent variables is still liable to be discriminatory in effect. Although the correlations are more easily identifiable, they are more difficult to eliminate as cleansing data of all proxies would leave little or no valuable data to be analysed. (Chapters 7 and 11) It also shows the depth of societal stratification; in Rieder's words: 'The problem, here, is not that data mining can be biased, but that, after centuries of inequality and discrimination, *empirical reality is biased*.'[65] Still, predictive analytics often exacerbates the problem by whitewashing those biases, whilst perpetuating inequalities under the cover of impartiality and objectivity. Of course, additional biases may also be built into the models. Furthermore, predictive algorithms are also not neutral or objective in so far as the goal-oriented perspective of the corporate or governmental profiler drives the choice of data and its interpretative framing. A government concerned with securing a maximum level of public safety is likely to define 'recidivism' or riskiness more expansively than one focused on rehabilitation, and will select and interpret data with that objective in mind. A corporation's algorithmic model for hiring decisions may, at times of heightened competition, emphasise ruthlessness over competence. A predictive model for creditworthiness might prioritise profit over affordability. These perspectives provide 'interested readings of reality', rather than impartial descriptions.[66] They do not aspire to any 'objective truth' but to an instrumentalised vision of the past to make useful judgements for the future.

Second, even if not 'true' in any objective sense, algorithmic predictions may or may not be accurate. If the model increases profits or reduces expenditure, it is valid; it works. The accuracy of data-driven profiling and attendant predictive practices is measured against subsequent individual consumption or behavioural choices. Did the user click on the recommended news story, film or advertisement, did she default on the loan, defraud the insurance company or buy the product with the increased personalised price? Did the accused reoffend; and did the employee become the rain-maker? One objection is that mistakes can be costly especially in grave contexts, such as sentencing of offenders, creditworthiness assessments or employment decisions. This is not unique to predictive algorithms (and present in all predictions about future human actions drawn from non-universal generalisations) but arguably aggravated here as the outcomes are often not contestable (see below). Still, the more accurate the algorithmic prediction, the greater its legitimacy against alternatives. A more profound objection against predictive algorithms and their proliferation across societal domains – justified by their (assumed, for the time being) superior accuracy – relates to the underlying assumption that they do no more than actualise a future that would have occurred in any event. If they turn out to be largely accurate, interference with reality is marginal. Yet, is this really the case? Predictive practices do not simply 'follow' expected futures, but in the course of implementing them intervene, encroach, manipulate and *make* these futures. As early as 1988, Jonathan Simon commented that actuarial practices 'cannot be dismissed as merely forms of knowing, when to be known is to be subject to significant alterations in life opportunities.'[67] By the same token, predictive algorithmic practices are not passive, but active in nudging the profilee towards the profiler's choice of pre-destinies,[68] whilst foreclosing other opportunities. An offender with a predicted high risk of recidivism is deprived of the chance to enact a different future of law-abiding behaviour; a social media user targeted with particular political messages is deprived of alternative perspectives on the subject-matter. The effect of personalisation practices is to 'normalise' populations within sub-groups. Lawrence Lessig's take on data-driven 'normalisation' (a Foucauldian concept associated with disciplinary regimes, e.g. schools or prisons, to institutionalise populations) is this: 'The observing will affect the observed. The system watches what you do; it fits you into a pattern; the pattern is then fed back to you in the form of options set by the pattern; the options reinforce the patterns; the cycle begins again.'[69] Mireille Hildebrandt thus observes that although customisation 'may seem the opposite to normalisation, in fact has a similar effect.'[70] It is not the profiler that adjusts to individual uniqueness, but rather individuals are – after an initial impetus of data – fitted into the profiler's instrumentalised patterns. Uniqueness is supressed; everyone is *like* others in crucial respects. It is not the profile that is 'accurate', but predictive analytics cajoles the individual into becoming 'accurate' to fit the pattern, into becoming compliant. (Chapters 2 and 3)

That having been said, actuarial practices present a subtler and more insidious form of normalisation than that exerted by the disciplinary institutions Foucault had in mind. Simon argued for the strategic distinctiveness of actuarial practices: 'Rather than seeking to change people ("normalize" them…), an actuarial regime seeks to manage them in place… While the disciplinary regime attempts to alter individual behavior and motivation, the actuarial regime alters the physical and social structures within which individuals behave,'[71] and thereby increases the efficiency of power through making populations more docile and manageable.[72] (Chapter 3) Still, predictive practices impact on, and shape, individual identity, including subjectivities about (group) belonging, or the lack of belonging: algorithmic or actuarial groups have 'no experienced meaning for the members, and therefore lack the capacity to realise common goals or purposes.'[73] Whilst stereotyping in the analogue world generally entails reflexive communications between profiler, profilee, the stereotyped group and the community, which generate a sense of belonging and internal solidarity within the group, algorithmic groups are often artificial, seemingly arbitrary, opaque and transient aggregates.[74] (Chapter 2) This 'makes it more difficult for group subjecthood to develop (or reproduce itself)'[75] and undermines the possibility of collective practices of resistance (see below) which in turn also reinforces their apparent accuracy.

Third, accuracy claims legitimising algorithmic profiling also have repercussions for moral agency, free will and normative domains. Predictive practices are in substance, if not in name, enabled by assumptions of character essentialism. (See Front Cover of the Book) Nicola Lacey commented: 'new technologies in fields such as neuroscience and genetics, and computer programs that identify crime "hot spots"… offer, or perhaps threaten, yet more sophisticated mechanisms of responsibility attribution based on notions of character essentialism combined with assessments of character-based risk, just as the emerging sciences of the mind, the brain, and statistics did in the late nineteenth century.'[76] If individual preferences and behaviour can be foretold 'accurately', it is tempting to conclude that the human actor is after all not the autonomous decision-maker the Enlightenment ideals of human rationality and freedom envisaged. The implications of this are stark, albeit not unprecedented. In criminal justice, forms of character essentialism have long grounded predictive practices that draw deterministic inferences from the delinquent's past to her future behaviour, in an uncomfortable tension with moral agency as the foundation of criminal responsibility and punishment. (Chapter 8). Liberal democracy and the market economy are equally dependant on the presence of autonomous citizens and consumers that can make rational choices between competing political parties and manifestos, or competing goods and services. Whilst in natural sciences, an overarching theory facilitates and constitutes the jump from 'is' (sun rose yesterday and today) to 'ought' (sun rise will rise tomorrow), within the legal and other normative domains, the notion of free choice is a moral imperative that prevents precisely such deterministic reasoning. Free choice entails the possibility of future difference, unexpectedness and new-ness. Importantly, the presumptive existence of personal autonomy (and an underlying understanding of human individuality as open-ended) allows for the possibility of normative demands in the first place. As such, moral agency is a necessary political requirement, even a necessary political fiction, not amenable to empirical disproof by algorithms or otherwise, no matter how great their apparent 'accuracy' is. Within a political and moral community, the open-endedness of human individuality is also essential for the possibility of collective betterment, premised on an understanding that the future is not, need not be, a replication of the past. Such betterment tends to lie in 'unknowable and unpredictable outlier-events' which are wholly outside 'accurate' statistical framings of reality.[77]

1.3.3 *Contesting Big Data Profiling within Spaces of Contestation*

The contestability of algorithmic processes and outcomes, and their reflexive impact on existing spaces of contestation, are likely to emerge as an overall touchstone for their differential legitimacies.[78] Contestation takes different forms in different social domains, but goes some way towards enlisting reasoning and explanations of and for the profiling, and could in principle discipline the uses and nature of predictive analytics. The source of the imperative for contestability varies across social spheres. In the *scientific community*, contestability is an integral part of the scientific method, and can be found explicitly in Karl Popper's concept of falsification that provides for the existence of scientific *knowledge or truth*, but always on a provisional basis, as long as it has not been falsified. In fact, according to Popper, the possibility of falsification is the hallmark of science and scientific knowledge as opposed to non-scientific ones, such as psychoanalysis.[79] Against this reading, insights of big data analytics are not, as such, falsifiable (and in that sense not 'scientific'), considering that algorithms deliver probabilities based on past patterns (facts) rather than (dis) proving universal propositions (normative claims). Even where the predicted probabilities are not borne out against new data sets, for example, Google's flu predictions,[80] and thus false, in the absence of a universal and grounded claim there is no theory that could be 'falsified' in the Popperian sense. This does not mean that these insights cannot be informative or useful (including in the development of theories), but rather that their standing as scientific knowledge or truths needs to be treated with caution. This holds significance beyond science in that data-driven 'scientific' knowledge and its methods routinely inform, for example, legal and political reasoning, propped up with the claim of 'scientific authority'.

In the *legal sphere*, the imperative of the contestability of governmental decisions flows from the State's unique power over individual life and liberty (classically expressed as the state's monopoly on the legitimate use of violence) and oversight in administering public life, and is designed to stem abuses of that power. The contestability (or reviewability) of governmental decisions is integral to the rule of law and actualised in a host of constitutional conventions, rights and guarantees that create spaces for individual or collective contestation. The right to judicial review of administrative decisions, the right of defence,[81] as well as data subject access rights are prime examples of individual rights to contest governmental decisions that affect the individual, underwritten by the understanding that such contestation makes for better decisions with greater legitimacy. Public decision-making based on black-box technology is thus, by its very nature, an anomaly. Its problematic is put in sharp relief within criminal justice, where data-driven profiling of delinquents falls uncomfortably between the countervailing forces of the *efficient* pursuit of public safety (economic perspective), on the one hand, and the presumption of innocence and moral agency as a basis for criminal responsibility, on the other hand. (Chapter 8) In the US case of *State of Wisconsin v. Loomis* (2016)[82] (Chapter 11 and 15) the Wisconsin Supreme Court upheld the denial of parole and consequential six-year prison term (for a drive-by shooting) which was based, in parts, on the 'Correctional Offender Management Profiling for Alternative Sanctions' black-box algorithm, otherwise known as COMPAS, that had classified Loomis as high risk to the community and of recidivism. For the court, it was not fatal to the defendant's constitutional due-process right, that neither the sentencing court nor Loomis had any insight into the workings of COMPAS to review the risk assessment for 'accuracy and scientific validity' – in light of the facts that the tool was only used to corroborate the judge's opinion *and* that Loomis had known the personal information that fed into the algorithm (which arguably also gave him some derivative insight about the algorithm's variables.)[83] The court's attempt to trivialise the tool suggests a keen awareness of its poor fit with the demands of a fair trial, which at the very minimum would require a reasoned decision (even 'black-box' jury decisions are foregrounded by testing of opposite narratives in the adversarial trial). Still, it approved the legitimacy of COMPAS, and thus, in the end, efficiency and blind knowledge trumped due process and articulated reasoning. Collective contestation to these algorithmic tools is unlikely by a public that is increasingly habituated to criminal justice as instrumentalist, preventative risk-management administration towards 'law and order' as opposed to the traditional retrospective, individualised model focused on moral accountability and just punishment, enacted through a trial that serves as a communicative process between defendant, state and community.[84]

In the *political domain*, contestability lies at the heart of democracy and democratic accountability, most prominently manifested in representative government, free elections and free speech protection. John Stuart Mill in reflecting on representative government insisted on the 'function of Antagonism' which, if unfulfilled, would condemn a 'government to infallible degeneracy and decay'.[85] Antagonism serves progress: 'No community has ever long continued progressive, but while a conflict was going on between the strongest power in the community and some rival power… When the victory on either side was so complete as to put an end to the strife, and no other conflict took its place, first stagnation followed, and then decay.'[86] Similarly and overlapping, the marketplace of ideas rationale for free speech protection is animated by the notion that the best or most truthful ideas will emerge victoriously in the free and robust competition (or contestation) of ideas and opinions.[87] Although the reverse may well be the case (i.e. the marketplace of ideas produces rather than reveals 'truths'), in approach it resonates with the concept of falsification in the scientific community. And yet again, personalisation or data-driven political micro-targeting provides for an uneasy fit with the public sphere and political deliberation, and at best disrupts and at worst diminishes existing practices of contestation. First and most importantly, unlike in the legal context, political micro-targeting taps into user preferences, and so almost inevitably incapacitates resistance to itself. Individuals have no or little incentive to question the accuracy or appropriateness of the profiling or personalisation practice, that is continuously adjusted in light of feedback loops. Second, although the overall effect of micro-targeting on the public sphere as a shared space for political deliberation remains ambivalent (Chapter 13), the problematisation of filter bubbles and echo chambers arises from a concern that micro-targeting profoundly undermines the practice of testing and contesting individual political standpoints through exposure to alternative narratives – with strong self-reinforcing dynamics.[88] (Chapter 17) The lack of exposure to such alternative narratives due to personalised context arguably generates more insular, polarised and extremist political perspectives, making them even less amenable to challenge. Thus third, increased political homogeneity and polarisation within echo chambers translates, at the collective, heterogeneous level, into a weakened willingness and capacity to communicate across political sub-communities, and thus tends to diminish social cohesion and conflict resolution, both of which traditional mass media fostered as a prerequisite for effective democratic governance.[89] Thus Cass Sunstein has argued that citizens in a well-functioning democracy ought to be exposed to *chance encounters* and to *shared experiences* which act as social glue, stressing affinity over difference, necessary for solving social problems.[90] Both demands are diametrically opposed to targeted personalised experiences, and up against a powerful alliance of commercial, political and individual interests in the practice of personalisation.

In the *commercial sphere*, contestability is implicit in the idea of the market which is, in its very conception, a space of contestation between providers, enacted by consumers through consumption choices freely and autonomously made and who thereby allocate resources to the 'best' providers. So, much like in the scientific, governmental and political arenas, market contestation also performs a type of 'quality control' with consumers as final arbiters. Whilst data-driven profiling and personalisation are apparently wholly in tune with such market contestation, in fact they undermine the market in significant ways – and again with the blessing of users. *First*, as Nick O'Donovan explores in Chapter 4, data-driven personalisation exerts strong secondary network effects that have led to further online concentration with a diminishing choice for consumers, especially amongst non-profiling providers. *Second*, consumers exercise their autonomy in favour of data-driven personalisation in an environment that is deeply hostile to alternative (and contesting) choices and nudges them towards personalisation, often in non-compliance with the General Data Protection Regulation[91] (Chapter 5) but not necessarily so. Against the immediate personal benefits gained (e.g. access to the site or free use of a service), the distant and often collective harms caused by mass algorithmic profiling, for example, filter bubbles, user-pay models, surveillance, manipulation, pale into insignificance. Facebook's 'emotional contagions study' of 2014 involved 689,003 users and showed how easily Facebook could manipulate the emotions of its subscribers.[92] Although this study was 'corporate research' in response to popular narratives,[93] in fact Facebook's core business lies in continually adjusting its algorithm to increase user time spent on the platform ('stickiness') and decrease buying resistance. The research caused outrage at the time, but did not lead to a mass exodus of its subscribers, as the collective and distant harms failed to trump the immediate personal gains. In that sense algorithmic profiling presents a classic tragedy of the commons, or collective action, problem. Even on a personal level, the collection of personal micro-data points drawn from online behaviour that are generally by themselves neither sensitive nor significant, does not easily translate – in the mind of users – into highly sophisticated individual profiles that may be used across a range of purposes from insurance to pricing to credit risks, and become virtual alter-egos which are hard, if not impossible, to escape. For privileged users, these virtual alter egos may give them significant leeway. Once in place, personalisation, which is designed to break down consumer resistance (i.e. create zero buying resistance[94]) as continuously perfected through feedback loops, becomes fully self-perpetuating, and thus pre-empts contestation. (See Chapter 17) The sheer profitability of profiling also makes corporate ‘AI ethics’ an unlikely candidate for (self)disciplining these practices. (Chapter 14) *Third*, a ‘personalised’ market is a highly fragmented market and in fact no marketplace at all; it fails as a communication network within which consumers can get (price) signals that would enable rational decision making and collective action that are defining features of a market. (Chapter 6) Typically, personalised pricing (or price discrimination) disempowers consumers as market participants, given the absence of stable reference points (i.e. the standard price offered to all consumers by a provider) against which buying choices may be made.[95] (Chapter 10)

Against these dynamics, any legal attempt to empower consumers and citizens individually, as the General Data Protection Regulation does as a primary strategy, is immediately met by the resistance-breaking features underlying personalisation. In the commercial context, individual contestation of profiles, similar to the challenge in *Loomis*, is likely only in respect of more significant transactions with an obviously negative outcome, for example, a rejected credit, employment or insurance application. In these very limited contexts (considering the overall ubiquity of personalisation), Article 22 of the GDPR might be useful as it gives profiled subjects the right to human oversight over ‘significant’ automated decisions,[96] including ‘meaningful information about the logic involved [in the algorithm], as well as the significance and the envisaged consequences [of the profile] for the data subject.’[97] This entitlement does not extend to an explanation for the actual decision, or normative justification, but would probably entail information about variables governing the predictive algorithms and their relevance to the decision, thus amounting to something *vaguely* approaching causation, or normative justification.

In summary, the use of predictive analytics has, in different social domains, encountered and, more or less successfully, disabled resistance to itself and thereby also chipped away at the broader spaces of contestation, which traditionally have served core *public values*, such as promoting knowledge, accountable government and functioning markets. Yet, the possibility of contestation also enfranchises the individual by allowing her to become an active participant or critical listener in processes and decisions that have an impact on her life. The inscrutability of profiling algorithms in criminal justice is blatantly problematic as its attendant decisions have an immediate and significant impact on individuals. The systematic exposure to mundane algorithmic personalised outcomes shrouded in darkness is perhaps even more challenging precisely because their all-embracing effects are more insidious, diffuse and evasive. Daniel Solove has argued for the inscrutability of personal data usage as a core harm that privacy is, or should be, concerned about. Using Kafka’s *The Trial*, he has shown how – beyond the harms caused by a surveillance environment when personal data is continuously collected – the inscrutability of the storage of data, its analysis and use creates a ‘suffocating powerlessness and vulnerability’ that repositions the individual *vis-à-vis* the state: ‘a bureaucracy with inscrutable purposes… uses people’s information to make important decisions about them, yet denies the people the ability to participate in how their information is used.'[98] His commentary was addressed to government but arguably extends to private actors whose inscrutable data practices are in their exertion of impersonal domination equally harmful,[99] particularly where those actors control the infrastructure of collective social, economic and political life. (Chapter 4) In the private sphere, the collection of non-traditional non-volunteered data, its aggregation and open-ended secondary uses (e.g. 'All data is credit data' Chapter 7) magnifies inscrutability and, by implication, the power asymmetries between profiler and profilee. It is this profound asymmetry that undermines the legitimacy of stereotyping which, as argued above, is *prima facie* necessary and useful. This asymmetry also means that whilst stereotyped individuals are in the analogue world, at least in some circumstances, able to participate in the creation of their own stereotype or contest it subsequently, the inscrutability of algorithmic decisions largely prevents active participation in, or contestation of, stereotyping. The individual is kept out of the loop in the processes and decisions that affect his life; or, in Rieder's words, kept 'in the conditions of paranoid meritocracy, constantly wondering whether their practices and preferences signal their adherence to "economic morality."'[100] Corporate actors – and derivatively governmental actors, considering the amount of data sharing – know us *intimately* and much more closely than we know them. Such intimate knowledge is neither harmless nor *prima facie* legitimate. It amplifies corporate and governmental power over consumers and citizens in a reversal of existing understandings of effective democracy and markets, which, even absent abuses, reshapes social relationships. The emergent judicial recognition of the non-domination principle, as advocated by academics as a new privacy standard, is a small tentative step towards acknowledging these paradigmatic shifts in power differentials and redressing them.[101] However, much wider systematic thinking about profiling and personalisation practices will be needed to retain and regain the foundations of a humanist digital society, grounded in individual and institutional responsibility, reason and articulated reasoning; individuality, community and solidarity; and communication as a means for expressing conflicts and work towards their resolution.

1.4 CHAPTERS: THE VOICES OF SUBJECT-MATTER EXPERTS

This collection contributes to the live debate of data-driven profiling and personalisation that has already attracted some impressive scholarship.[102] The volume's particular contribution lies in creating room for the voices of subject-matter experts from various disciplines within law as well as from human geography, philosophy, behavioural economics and criminology, who are not first and foremost 'technologists'. This reflects the philosophy and ambition behind the collection to construct this new phenomenon of data-driven profiling and personalisation, not as a technological problematic to be analysed and 'solved' by computer specialists, IT law or policy experts, but rather as a social, economic and political phenomenon that can and must be understood through existing subject-specific discourses within which it falls. It is through these discourses that compelling continuities and discontinuities with past legal approaches, economic constructs, political, sociological and jurisprudential narratives and underlying ideologies may be observed and critiqued. Equally, the volume speaks to the pressing need for the big data phenomenon, that is sweeping across many societal domains, to be integrated within existing disciplinary scholarship *and* across them.

Running these different discourses about different manifestations of the same phenomenon next to each other is insightful, not least because of the divergent terminology used to describe it. What is known in the market under the enticing labels of 'personalisation', 'customisation', 'optimisation' or 'smart' technology, becomes 'micro-targeting' in the political context, a term that gives a sense of the aggressive and exploitative dimension of the practice. In the legal and criminal justice environment, the terminology 'predictive policing', 'algorithmic profiling' or 'actuarial justice' brings out the more overtly controlling aspects of algorithmic profiling as well as its grounding in the 'scientific' method. In the medical context, the language of 'precision' or P4 medicine (referring to 'predictive, preventive, personalised and participatory') arguably emphasises both the technical nature of the approach and the benefits it brings to patients. The diversity of the terminology provides a snapshot of the particular framing and values that corporate or governmental profilers seek to highlight, but also shows traces of the value that can be found in most profiling practices more or less strongly.

The volume is divided into four parts. It starts and finishes with overarching theoretical accounts of algorithmic personalisation practices and offers in the two middle parts, first, general key themes that emerge from specific legal environments, and, second, a range of social spheres and discourses in which these themes are reconstituted and adjusted within particularised contexts. All in all, the emphasis throughout the volume lies in presenting different disciplinary perspectives in antagonism and rapport with each other. A unifying theme running through the chapters in the first part is the profound power unleashed by big data profiling technology, and its impact on long-standing social structures, modalities of governance and market constellations. In *'Personalisation and Digital Modernity: Deconstructing the Myths of the Subjunctive World'* **Kieron O'Hara** situates data-driven personalisation within a sociological narrative of modernity and its Enlightenment values of rationality, progress and individuality, which has given way to *digital modernity*, characterised by 'communication… supercharged by always-on networked linking using digital technology… the migration of many interactions online… exponentially positive network effects… [and] the capture and reuse of data as a resource.' O'Hara's focus is on the individual who has his world moulded around him through personalised recommendations. Personalisation replaces authentic choice that served as a core tenet of modernity –

and necessarily requires privacy. For digital modernity, choice is now 'the prerogative of the data infrastructure which constructs the personalised world.' The data infrastructure knows much better what one *should* prefer, and also requires the abandonment of privacy. O'Hara provocatively sets the tone for later discussions that seek refuge from the excesses of profiling in data protection law, by showing quite how systematically privacy has to be and in fact is abandoned to make space for this brave new digital world. The implications of the datafication for new modalities of government – in close proximity to or through the market – are explored by **Marc Welsh** in '*Personalisation, Power and the Datafied Subject*' from a Foucauldian perspective. Here the individual is an important cog in the wheel of the governmental project of 'improving populations'. The individual becomes the locus for the construction of the datafied self, through which self-disciplining control can be exerted. Personalisation technology shifts responsibility for 'correct' forms of actions and behaviours to individuals, whose co-option in algorithmic governmentality is not forced at all, but enticed by rewards, like lower insurance premiums for good driving behaviour (driving metrics) or for healthy lifestyle behaviour (health metrics). Consent is the enabler, power asymmetries the starting and end point: 'The data-poor voluntarily proffer their data to be monetized by companies who combine it with the data lives of others to produce population wide correlations and inferences that can be utilised to generate profit or reduce losses through forms of algorithmic government.' In fact, algorithmic personalisation amplifies those asymmetries by weakening markets. **Nick O'Donovan** in his chapter on '*Personal Data and Collective Value: Data-Driven Personalisation as Network Effect*' shows how algorithmic personalisation exerts subtle secondary network effects of a qualitative type that lead to even more intensive concentration in markets already heavily impacted by primary network effects: the more intensive and sophisticated the data practices, the more fine-tuned the personalised recommendations, and the more willing, and less resistant the consumer who in any event has fewer choices. And, as with all network effects, it has strong self-reinforcing dynamics.

Against these deeply critical and dystopian social science accounts of data-driven personalisation, the second part of the volume hears the voices of legal scholars whose disciplinary methods, toolkits and temperaments mean that the tone of the conversation becomes more practice-focused, technical and cautious, even if the verdicts are ultimately not dissimilar. Existing legal regimes and doctrines, whether data protection, contract, antidiscrimination or criminal law, are profoundly challenged by algorithmic prediction and personalisation. Not only do they fail to act as a break against unfair or exploitative predictive practices, but they have their regulatory integrity and objectives undermined by the structural and operative distinctiveness of algorithmic personalisation. An obvious starting point is data protection law, and in particular the GDPR, that has been much celebrated for its regulatory rigour. Yet, **Michèle Finck's** analysis in '*Hidden Personal Insights and Entangled in the Algorithmic Model: The Limits of the GDPR in the Personalisation*

Context' shows why neither a framework based on consent nor other user empowerment effectively disciplines corporate algorithmic personalisation. The chapter also conveys a strong sense that binary divisions or understandings between sensitive and non-sensitive data, individual and group data, personal and non-personal data simply fail to do justice to the workings of big data analytics and belong to a bygone analogue, small-data world. In a similar vein, **TT Arvind** in '*Personalisation, Markets, and Contract: The Limits of Legal Incrementalism*' argues that the phenomenon of algorithmic personalisation presents a paradigmatic challenge to both privacy and contract law. Privacy conceptions had never before so systematically been underwritten by contractual arrangements and the ability to commodify one's privacy. Yet, contract law itself is challenged by data-driven personalisation. A traditional personalised contract (e.g. the tailored suit) assumed a joint project and a two-way relationship between buyer and service provider, whilst current personalised contracts are de-relationalised and so no longer moderated by such two-way dependency. A personalised, de-relationalised contract creates a one-way dependency or informational asymmetry that profoundly undermines the user's effective participation in the market. In '*'All Data Is Credit Data': Personalised Consumer Credit Score and Anti-Discrimination Law*' **Noelia Collado-Rogriguez and Uta Kohl** explore, with reference to big data use for consumer credit scores, whether anti-discrimination law offers any realistic opportunity to review algorithmic predictions. Whilst the concept of indirect discrimination – focused on the actual effect or outcome of a practice – offers in principle a viable method for overcoming the opacity of black-box algorithms, it can do little to overcome the structural socio-economic disadvantages that sit at the root of much unequal treatment. Disconcertingly, such inequality is potentially aggravated by big data credit score models that follow the logic of 'all data as credit data' which threatens to apply an all-encompassing judgement of the individual to all social domains, regardless of their functional separation. Moving from civil to criminal law, **David Gurnham's** discussion in '*Sentencing Dangerous Offenders in the Era of Predictive Technologies: New Skin, Same Old Snake?*' places novel predictive algorithms that assess the dangerousness of offenders for sentencing purposes within a long-standing practice of actuarial risk assessment. Although predictive technology is in that sense merely a sophisticated version of the old, it powerfully underlines its fundamental mismatch with liberal principles of retrospective, responsibility-based punishment.

The third part of the book situates data-driven personalisation within various social domains and disciplinary discourses. The richness of the different languages and conceptual framings illustrates both the textual variety and the common nature of the problematics. Starting off with '*'P4 Medicine' and the Purview of Health Law: the Patient or the Public?*', **Keith Syrett** traces precision or personalised medicine back to the inception of the Human Genome Project in 1985 and a systems approach to biology that has recently been augmented by the digital revolution. Significantly, the rise of personalised medicine mirrors a shift from medical paternalism to patient choice as a central tenet of UK medical jurisprudence – in that sense law (and ethics) act as key facilitators of precision medicine. Syrett then argues that personalised medicine's fundamental focus on the particular patient, as supported by legal and ethical trends, underplays the important collective nature of health and its social stratification and thus must be treated with caution as a wholesale welcome development. Different yet similar, **Joost Poort and Frederik Zuiderveen Borgesius** explore in '*Personalised Pricing: The Demise of the Fixed Price?*' the practice of price discrimination based on predictive algorithms and its underlying basis in economic theory. Although the net welfare impact of personalised pricing is not clear-cut, the more prices are personalised, 'the more welfare will generally shift from consumers to suppliers.' Surprisingly, the authors' empirical studies show that consumers are overall not supportive of price discrimination even when it works in their favour. This suggests either an intuitive commitment to collective fairness or, more likely, a rejection of a highly fragmented market within which making rational buying choices is fundamentally undermined. Although such user rejection is in theory accommodated by the GDPR's requirement of consent, whether price discrimination is, or can be, effectively stopped remains shrouded in the opacity of online pricing practices. Moving from law disciplining data-driven personalisation, to data-driven personalisation employed as a disciplining device, **Pamela Ugwudike** takes a criminological perspective on the rise of predictive algorithms in criminal justice. In '*Data-Driven Algorithms in Criminal Justice: Predictions as Self-fulfilling Prophecies*' she critiques their fairness by arguing that 'profiling algorithms generate labels that counterproductively evoke a self-fulfilling prophecy and foment future criminalisation.' Biases against minorities – already ingrained in the data sets and the algorithmic models and then reinforced through the profiling – are not just problematic from a penal perspective, where accuracy claims must at the very least be supported by evidence of their differential validity. A social justice perspective can also expose the structural unfairness of predictive technology, and its grounding in historic social and economic disadvantage. 'Smart city' developments – discussed by **Daithí Mac Síthigh** in '*From Global Village to Smart City: Reputation, Recognition, Personalisation, and Ubiquity*' – subtly merge the commercial functionality and controlling dimension of big data analytics. In smart city projects, the ubiquitous physical presence of algorithmic technology is promoted and justified as a more efficient way to 'manage the relationship between the responsible authority and individual residents or other users' mediated by privately owned technology. Mac Sithigh's discussion of the Chinese social credit system and various facial recognition technologies, as enabling devices for effective service delivery within city environs, suggests that policing functions are never far behind the creation of corporate digital infrastructure. The smart city simultaneously enacts a utopian and dystopian vision of a technologically infused society where government and corporations 'know' in detail the individual and the group and act upon that knowledge. A different, but equally powerful, merger of private and public interests occurs in the course of political micro-targeting, as discussed by **Normann Witzleb and Moira Paterson** in '*Micro-targeting in Political Campaigns: Political Promise and Democratic Risk.*' The Facebook/Cambridge Analytica scandal of 2018 provides a natural starting point to explore the virtues and vices of targeting individuals with personalised messages during political campaigns. The authors argue that applying data protection law to political micro-targeting (i.e. lifting the current derogations and exemptions) would provide a useful restraint and garner the benefits and minimise the costs of such personalisation. Yet, perhaps their arguments are too optimistic – considering, on the one hand, Finck's exposition (see above) about the problems associated with consent and the structural peculiarities of big data analytics not acknowledged by data protection law and, on the other hand, the powerful alliance between commercial, political and private interests in favour of micro-targeting.

The final part of the collection is confidently entitled 'The Future...' suggesting that we – as data-limited humans – may *know* the future of data-driven personalisation and its impact on society, even without the aid of a predictive algorithm. What the chapters make clear is that whilst we may not be able to predict what the future *will* be, we can have views of what it *ought* to be. This is where we infinitely outperform even the most complex algorithms: in making normative judgements about the good life and the contours of a society that would support it. This part starts off with **Andrew Charlesworth's** discussion on '*Regulating Algorithmic Assemblages: Looking Beyond Corporatist AI Ethics*' about the confidence that we might place in corporate AI ethics as a mechanism for restraining the excesses of data-driven personalisation, given its dominant position in the current discourse on regulating technology. Situating 'AI ethics' within traditions of corporate social responsibility and institutional ethical frameworks shows its systemic shortcomings and inability to be truly Other-regarding. The chapter further argues that making 'ethical' corrections to AI applications rarely, if ever, addresses their wider societal consequences which arise from their deep integration into social structures, as captured by the idea of 'algorithmic assemblage'. If corporate ethics is a weak answer, **Konstantinos Katsikopoulos's** proposal might be more fruitful, at least in regulatory contexts. In '*Scepticism about Big Data's Predictive Power about Human Behaviour: Making a Case for Theory and Simplicity*' he argues that simple algorithms, supported by theory, do not just have the virtues of intelligibility and thus allow for transparency and accountability, but are also often in performance at least as good as their complex black-box equivalents. This argument is important in respect of predictive technology within the legal and regulatory environments, but holds less force within commerce or political advertising where the corporate bottom-line and party political success are the clear and simple arbiter of whether personalisation 'works'. Another 'process' within and against which algorithmic personalisation may be judged is the role of communication and language in society. In '*Building Personalisation: Language and the Law*' **Alun Gibbs** argues that algorithmic personalisation replaces and competes with language; technology delivers choices and results, but not arguments, explanations or justifications. Yet, it is language that underpins and supports personhood, agency and authentic choice which create social meanings and solidarities and are the key building blocks of our wider understanding of constitutionalism as a political way of life. The more widespread the adoption of personalisation technologies in the building of the 'self', the more we endanger and deconstruct those building blocks and, with them, our political way of life. **Jacob Eisler's** '*Conclusion: Balancing Data-Driven Personalisation and Law as Social Systems*' synthesises the chapters of the volume, and offers a new perspective, by using the socio-legal approach of systems theory. He argues that the real force of personalisation is that it becomes an internal component of the self-perpetuating systems it touches: society as a whole, and even more intimately, individual persons themselves. Its deep integration into these systems illuminates two themes of this volume: why data-driven personalisation's impact is so difficult for standard consent-based mechanisms of legal interpretation to manage; and why the power that elite actors have over the mechanisms of algorithmic personalisation is so insidious. Personalisation does not merely affect society; it becomes part of its constitution. It does not merely affect persons, it becomes part of their identity and self-constitution. Law may counterbalance personalisation, but to do so effectively it must ensure that practices and norms of personalisation do not infiltrate it, as they have infiltrated so many other domains of our society.

NOTES

* Many thanks to Nick O'Donovan, Jacob Eisler, Jörn Werner and Carrie Fox for insightful comments and suggestions.

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7 Bernard E Harcourt, *Against Prediction* (University of Chicago Press 2007); Ben Bowling, Shruti Iyer, 'Automated policing: the case of body-worn video' (2019) 15 *International Journal of Law in Context* 140, 153ff.
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11 Shoshana Zuboff, *The Age of Surveillance Capitalism* (Profile Books 2019) 8.
12 John Rawls, *A Theory of Justice* (Harvard University Press 1971); Michael Walzer, *Spheres of Justice* (Basic Books 1984).
13 Julia Lawn and others (eds.), *Privacy, Big Data and the Public Good – Frameworks for Engagement* (Cambridge University Press 2014).
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18 Schauer refers to these as universal generalisation which may be based on linguistic definition; for example, all bachelors are unmarried, or empirical observation, for example, all humans are less than 9 feet tall, in Frederic Schauer, *Profiles, Probabilities, and Stereotypes* (Belknap Press 2006) 8f.
19 Hildebrandt (n16) 21.
20 Vedder (n17) [emphasis added].
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33 Ibid. 100, 251ff.

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