



Article

Assessing Creditworthiness in the Age of Big Data

A Comparative Study of Credit Score Systems in Denmark and the US

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Abstract

The purpose of this article is twofold: first, we show how algorithms have become increasingly central to financial credit scoring; second, we draw on this to further develop the anthropological study of algorithmic governance. As such, we describe the literature on credit scoring and then discuss ethnographic examples from two regulatory and commercial contexts: the US and Denmark. From these empirical cases, we carve out main developments of algorithmic governance in credit scoring and elucidate social and cultural logics behind algorithmic governance tools. Our analytical framework builds on critical algorithm studies and anthropological studies where money and payment infrastructures are viewed as embedded in their specific cultural contexts (Bloch and Parry 1989; Maurer 2015). The comparative analysis shows how algorithmic credit scoring takes different forms hence raising different issues in the two cases. Danish banks seem to have developed a system of intensive, yet hidden credit scoring based on surveillance and harvesting of behavioural data, which, however, due to GDPR takes place in restricted silos. Credit scores are hidden to customers, and therefore there has been virtually no public debate regarding the algorithmic models behind scores. In the US, fewer legal restrictions on data trading combined with both widespread and visible credit scoring has led to the development of a credit data market and widespread use of credit scoring by 'affiliation' on the one hand, but also to increasing public and political critique on scoring models on the other.

Keywords

algorithmic governance, credit scoring, US, Denmark, critical algorithm studies, anthropology

Francis Fukuyama's notorious 1992 declaration that we should have reached the 'end of history' may very well be one of academia's most contested and refuted claims. Nevertheless, a somewhat similar claim about 'endings' has emerged once again, this time centered around the new markets for personal data and the increasingly central role of algorithms in everyday life: obtaining a bank loan, policing, health, insurance risk, and political campaigning. In her recent academic blockbuster, *The Age of Surveillance Capitalism*, Shoshana Zuboff (2019) suggested that algorithmic predictions may erode the most basic conditions of human life. The increasing use of algorithms and big data has spurred additional concerns among scholars in terms of the wide-ranging implications of these technologies for social life and personal privacy. Some studies address power asymmetries and breach of privacy (Larsson 2017; Zuboff 2019), others 'the black box' (Pasquale 2015), risk of unintended errors and the 'naturalization' of social discrimination and inequality (O'Neil 2016), while others emphasize the need for improved legislation and consumer empowerment (Larsson 2018). In this article, we contribute to this discussion about the organization and significance of algorithms in a 'data-driven economy' (Larsson 2018). Utilizing empirical examples from the US and Denmark on the usage of algorithms in credit scoring, we develop an analytical framework that moves beyond the prevailing theme of algorithmic analyses, which highlights how algorithms *create* social order (Katzenbach and Ulbricht 2019). Instead, we view algorithmic governance in a broader anthropological and empirical perspective. We define algorithmic governance as complex computer-based epistemic procedures, which structure the social in multiple ways and coordinate action based on rules (Katzenbach and Ulbricht 2019, 2). However, we broaden this definition to include a view on algorithmic governance as socially contextualized. In the article, therefore, we integrate two hitherto distinct perspectives: governance *by* algorithms (how algorithms themselves shape social life by profiling and automated predictions based on big data) and governance *of* algorithms (how legal and cultural contexts shape the form, scope, and impact of such automated predictions) (see Just and Lazer 2016). We focus on predictions related to the mathematical calculations in algorithms in credit scoring – and how the underlying operations of these predictions are themselves shaped by particular political, commercial and cultural contexts. In this article, therefore, we discuss how big data, personal data harvesting, and algorithms are employed in contemporary corporate markets of credit evaluation, banks, and lending companies. We have chosen to focus on credit scoring in the US and Denmark because they reveal different trajectories and configurations of credit scoring. The two examples can therefore serve to highlight the significance of contextual variations when analysing algorithmic governance.

The paper has three principal aims. First, to shed light on the particularities of algorithmic governance by means of an empirical analysis of credit scoring in two empirical contexts. Second, through comparison of the US and Danish practices, to show how particular contextual conditions (the development and form of the credit evaluation industry and legislative framework) constitute unique credit scoring regimes. Third, to use these insights to show common developments as

well as regulatory variations in algorithmic credit scoring and to further develop an anthropological framework for the study of algorithmic governance.

The Emerging Field of Critical Algorithm Studies

Over the last decade, a large number of scholars from several disciplines have worked towards unravelling the ‘black box’ (Pasquale 2015; Lupton 2016; Amoore 2018) of algorithmic operations and their social implications.¹ We have identified three predominant approaches in this literature: 1) studies of the power of algorithms, touching on issues of governance and the political effects of algorithms on citizens’ everyday lives, often in a prejudicial or discriminatory manner; 2) studies of the more technical workings of the algorithms themselves, and the way they in turn filter, order and transform central dimensions of life; and 3) studies of the embeddedness of algorithms in social and cultural contexts as a means of developing a specific anthropological approach. In the following, we review examples of these approaches in order to show how they help us understand algorithmic predictions from an explicitly anthropological and empirically-based perspective; we then show how our perspective can be applied to the domain of credit scoring.

The first body of work emphasizes the political and legal dimensions of the deployment of algorithms in contemporary society. Key issues include how different forms of discriminatory logics may be inscribed in the algorithms, the lack of transparency in the handling and circulation of data, and the vulnerabilities that are exacerbated through new surveillance practices (O’Neil 2016; Sumpter 2018; Zuboff 2019; Benjamin 2019). At its extreme, leading scholars have warned that algorithmic predictions may ultimately result in the loss of ‘the future tense’ (Zuboff 2019). Zuboff, for example, shows how surveillance capitalism relies on the harvesting of human experience which is turned into a market of predictive products and then, by way of behavioural modification, actively manipulates human decision-making. According to Zuboff, this erosion of human control and exercise of free will undermines the conditions of human future making (Zuboff 2019, 347). Her argument resonates well with the critiques of the predictive logics of algorithms related to predictive policing (Maguire 2018, 138) and the ‘conventional wisdom’ of algorithms’ impact on healthcare, education, insurance risk, and welfare provision (Lyon 2014). Other critics point to the lack of regulation that allows algorithmic operations to interfere in daily life in ways that are either authoritarian or dysfunctional. With first-hand knowledge of algorithmic decision-making processes through her work in the finance industry, Cathy O’Neil presents a devastating critique of the lack of legal oversight and audits that could curb the discriminatory effects of reigning predictive models within a range of disparate fields such as insurance, policing, education, penal system, and elections. The misuse of mathematics is all around us. The problem is

¹ For an overview of literature and studies see, <https://socialmediacollective.org/reading-lists/critical-algorithm-studies/>

not merely the false objectivity of specific algorithmic operations. Algorithms are always pre-configured according to a certain gaze or disposition that is often derived from the developers' and coders' perspectives. This algorithmic disposition, so to speak, reflects that of the bureaucrat, the bank clerk, or the actuary. The crucial difference, O'Neil (2014) argues, is one of scale as the algorithm transform decision making from something that takes places on the level of the individual into much larger scales and thus into what she calls, 'weapons of math destruction' (WMDs).

O'Neil's study links up nicely to the second group of algorithm studies, focusing on algorithms' more technological aspects. What is characteristic of these studies is that they often employ innovative methodological and ethnographic approaches (e.g. Clifton, Mulligan and Ramakrishnan 2006; Deville and Van der Velden 2016; Amoore and Piotukh 2015). One example is Deville and Van der Velden's (2016, 87) work on credit assessments, where they seek to reveal what they term 'the labour of machines: the automated, unseen, digital work undertaken by "trackers" (other terms include "bugs", "pixels", "tags").' In an attempt to mirror the machine or track the tracker, the authors employ a tracker detector device that can generate data and visual representations so as to unravel the dispositions and lending operations of different loan providers. While these studies reveal much using their novel methodologies, they tend to downplay the ways that these technologies shape the fields in which they operate. In their introduction to the edited volume *Algorithmic Life: Calculative Devices in the Age of Big Data* (2015), Amoore and Piotukh argue that we cannot make sense of big data questions and governance if we do not look closely into the sorting machines. While Amoore and Piotukh's algorithmic engagement clearly spans the technical and the governmental, their empirical focus is on rendering the technical visible. Algorithms, they argue, embody a new rationality. They institute new visibilities and invisibilities by altering 'the nature of human subjectivity and pushing the limits of what can be read, analysed and thought about' (Amoore and Piotukh 2016, 9). Such reconfiguration of visibilities has spatial, temporal, and governmental implications, the most important of which is the asymmetry of sight, and hence of power, thus re-actualizing the classic discussion of Jeremy Bentham's prison architecture, the Panopticon (see also, Katzenbach and Ulbricht 2019). Following Amoore and Piotukh, algorithms, machine learning, AI, and big data tend to be viewed as paradigmatic, comprising a rupture or radical change. Algorithms are now elevated to become the very key of a 'modern rationality', defining prevailing forms of calculation, determination, and categorization (Toraro and Ninno 2014). Algorithms, in this reading, are the new Panopticon. Other scholars remain more sceptical of such grand pronouncements (cf. Seaver 2018; Barocas, Hood, and Ziewitzs 2013; Neyland 2015). To mention but one example, Barocas, Hood, and Ziewitz (2013) identify a tension in the academic discussions on algorithms between designating the algorithms as powerful actors in contemporary society while stressing algorithms' strangely elusive and opaque quality. Such tensions, the authors argue, enable algorithms to become a kind of blank space or empty vessel for raising issues of technology and politics.

In a recent attempt to address this tension, Lange et al. (2019) have undertaken the task of studying financial algorithms ethnographically, notably by incorporating the organizational contexts within which algorithms operate (in this case proprietary trading techniques). Lange et al. list several challenges facing those who would study algorithms in their social, cultural and organizational context: first, algorithms rarely operate in the open; they are ‘obscure objects’ that are hard to access (Lange et al. 2019: 599). Because algorithms process enormous amounts of data at speeds that are impossible for humans to grasp, algorithmic ‘behaviour’ escapes our conventional ethnographic observation. Nevertheless, building on the work of Michel Serres, Lange et al set out to trace, map, and analyse the multiple kinds of possible subject-object relations that exist within the field of high-frequency trading (HFT). In this way, they neither render the algorithm as a direct extension of the trader’s will, nor do they depict the trader as entirely subjected to the algorithms’ operations.

From this vantage point, it becomes problematic to operate with a single, generalized approach to the study of algorithms. Can algorithms be detached from the domains in which they are deployed? As recently argued by the anthropologist Nick Seaver, algorithms *are* culture (Seaver 2018, 379). For Seaver, there is no algorithm without a human counterpart who designs and continually alters and reconfigures them. Algorithms are recursive (Kelty 2005) and agile, they adapt, and operators and programmers frequently emphasize their own, decidedly human opinions, reasoning and taste as vital for optimizing the algorithms. The idea that algorithms enslave or do bad things to people is a misnomer, asserts Seaver. People, not algorithms, exert their influence on people (Seaver 2018, 378). Accordingly, an anthropology of algorithms should attend to the mundane routines – such as those found in the accumulating processes of feedback loops – and to the connectedness and imagined disjunctions between the digital and the analogue, the algorithm and the person, as they are configured in discursive fields as well as in everyday practices.

Drawing on Seaver’s insights, we argue here that algorithms are embedded in the social and cultural fields in multiple ways. Unlike Seaver, however, we adopt a position that stresses algorithms as being more deeply embedded in social and organizational contexts, *beyond* the communities of developers and technicians. We build on Bloch and Parry’s approach, as they outlined their pioneering introduction to *Money and the Morality of Exchange* (1989). Bloch and Parry emphasize two fundamental aspects of money that we believe also apply to algorithms: embeddedness and fetishization. First, in the same fashion that Bloch and Parry discuss the embeddedness of money in society, we view algorithms as something more than yet another external technology that somehow disrupts a social system. Instead, we underscore the ways in which algorithmic operations derive from certain historical and cultural registers of calculation and prediction (Bouk 2015; Lauer 2017; Daston 2013; Guyer 2007). Second, Bloch and Parry identify a tendency to fetishize money. Here again, the parallels between money and algorithms are striking. Algorithms appear to have brought about a

comparable sense of fetishization among scholars and developers. In discussing the fetishization of money Bloch and Parry suggested two interconnected processes. On the one hand, Western money is *theorized* as having the power to disrupt and reconfigure social relations. On the other hand, this ‘dehumanizing’ power, the ability of money to act as a kind of acid that dissolving sociality can be historically related to Western discourses on money; hence, they can be understood as an *empirical* feature of money discourses in a Western context (Bloch and Parry 1989, 6).

Following this line of thinking, we do not understand algorithms as universal placeholders for a new ‘modern rationality’ nor as generic surveillance technologies. Rather, we view algorithms as integral to particular business models in different domains, and as such as part of *organizational logics with distinct historical trajectories*. While Seaver demystifies what is commonly understood as secrecy or *black box-ness* of algorithms, he overlooks the issue of how and why algorithms travel, where they come from, who owns them, and the workings of the markets to which they cater, and the markets for algorithms themselves. In trying to understand how algorithms move from one context to another, we seek to acknowledge the dis- and resonance of the particular and concrete operations of algorithms within broader historical and cultural domains in which predictive logics and practices operate (Guyer 2007). New technologies are folded into local ideas and practices of divination, risk assessment, calculation, prediction, fortune (De Col and Humphrey 2012; Pedersen 2012; Chu 2011; 2018; Elliot and Menin 2018). This is not to belittle the inequalities that algorithms create for people’s lives, nor do we wish to downplay the effects of automation and automated decision-making on major domains of social life such as welfare, policing, border management, etc. (Eubanks 2018; Benjamin 2019; Kaufman and Leese 2018). Rather, we wish to complement prevailing critiques by emphasising the ways in which the ‘rule making’ (Katzenbach and Ulbricht 2019, 2) principle of algorithms is influenced by different operational, legislative, and sociocultural contexts. To provide some empirical exemplification as to how this may work, we now turn to the field of credit scoring, describing the usage of algorithms in two different social contexts, the US and Denmark. For each case, we analyse the specific form of algorithmic governance and surveillance of citizens.

Credit Scoring as a Case of Algorithmic Governance

We use the domain of corporate credit scoring as a window into the emerging logics of contemporary algorithmic governance and related forms of surveillance and political regulation as practiced in Europe and the United States. In the US, the development of credit evaluation, credit assessment, and surveillance of individual consumers have a long history, starting with commercial credit reporting firms, whose evaluation practices from the nineteenth century have become defining of contemporary consumer credit reporting (Lauer 2017). The US history of credit evaluation, therefore, partly provides a counter-narrative to the commonly held assumption that today’s systematic, pervasive, personal, and

invisible surveillance is a recent phenomenon related to new technologies of harvesting of personal data, data brokerage, and algorithmic prediction products (cf. Larsson 2018; Pariser 2011). Credit evaluation has also historically included both the assessment of an individuals' financial resources and capabilities and moral character. Early credit reports from the beginning of the twentieth century included intimate details of people's domestic arrangements, personality, health, legal and criminal history and job performance (Lauer 2017). More recently, credit scoring has taken on a major element in the development of statistical risk scoring and marketing programs, drawing on massive datasets that create algorithmic predictions of the behaviours and commercial value of consumers (ibid.). Thus, the history of credit evaluation reflects a history of surveillance and moral evaluation of citizens as well as a more recent paradigmatic shift in the precise form that surveillance and moral evaluation takes.

The literature on financial credit scoring has hitherto largely focused on the US credit market and credit scoring systems. In recent years, however, the concept and business models of credit scoring have developed in other countries – in some cases with wide ranging effects.² In the following, we examine algorithmic governance of credit scoring in the US and Denmark. Our aim is to compare algorithmic-based credit scoring in each case and to discuss the specific forms of surveillance, social consequences, and issues related to particular modalities of algorithmic governance. Denmark has had a rather different history of commercial credit evaluation compared to the US and is now part of the EU regulatory regime, which includes the recent data protection directive, GDPR. The choice of these two countries provides a scope for comparison: we can question certain conventional assumptions about algorithms and show how each case is 'a "context" for the other' (Strathern 2000, 280; Lazar 2012). We thus follow recent trends of 'inductive comparison' (Melhuus 2002), by which we theorize not only differences between regimes, but rather how, taken together, these differences comprise the framework for understanding different dimensions of a broader cultural phenomenon (Moore 2005).

Although our focus is on the embeddedness and deployment of algorithms as an adjunct to organizational policies and 'proprietary trading techniques', the use of algorithms remains largely opaque to the public and is classified as business secrets by their proprietors. The black-box-ness associated with the algorithmic technologies therefore also includes the corporate or governmental forms they take in national contexts. The following empirical analysis of credit scoring algorithms in the US and Denmark relies on both document analysis from business and public sources and ethnographic interviews with people affected by credit scoring practices. The documentation also includes media accounts and legal documents although the combination of empirical data is a bit different in the two cases.

² China's appropriation of social credit scoring is a clear example of this development (Ohlberg et al. 2017; Kostka 2019).

In the US case, we draw primarily on secondary literature describing credit evaluation and the concrete empirical examples that they provide (Lauer 2017; O’Neil 2016; Hurley and Adebayo 2019). We also use marketing materials from credit scoring companies, online discussions on the websites Quora and Reddit, and documents from a 2019 congressional hearing. Finally, we draw on insights from 21 interviews with ordinary US consumers on everyday finances and their credit scoring experiences, carried out in 2017 and 2018.

For Denmark, fewer secondary sources have been available. We have included one article on the (lack of) credit evaluation by lending companies (Jørgensen 2015). In addition, our data consists of three magazines and newspaper articles on credit scoring by Danish Banks. We have also analysed privacy policies from two large Danish banks, a Danish documentary on lending companies from 2019, and legal documents on the EU data protection regulations (GDPR) and other relevant EU regulatory measures (2019). Finally, we have conducted one interview with an employee in a large Danish bank (carried out in 2019).

Credit Scoring in the United States

The vast majority of Americans rely on credit to make ends meet. With 70% of the American GDP as consumer spending, almost all major purchases (e.g., home purchase, car purchase, college tuition) entail some kind of lending arrangement and thus require a credit assessment from a bank, mortgage company or consumer lender (Lazzarato 2011, 19-20). Most lenders use the so-called FICO Score, which is a three-digit number based on a summary of people’s credit report, the purpose of which is to assess people’s creditworthiness and to determine the loan conditions.³ The FICO Score was created by the company FICO (Fair Isaac Cooperation), founded in 1956. FICO specialises in credit scoring services. Besides being the most used score among top US lenders, it is also applied in and adapted to other markets, such as the mortgage market (Poon 2009). To receive a FICO Score, consumers must actively use their credit, and their credit report must contain enough recent information such as payment history, amounts owed and delinquency incidents. Consumers can then increase their FICO Score through certain behaviour, such as meeting payment deadlines and using their credit cards but without using up too much of the available credit line.⁴ While promoted as a consistent, objective and fair assessment of credit risk based on five components⁵, online discussions on FICO’s own forum, my FICO Forums, the question-and-answer website, Quora, as well as on the website Reddit, indicate that consumers collectively reflect on the accuracy and validity of the FICO Score (Pasquale 2015). The importance of having a credit history and a good credit score is often

³ <https://www.ficoscore.com/about/>

⁴ <https://www.ficoscore.com/education/>

⁵ The five components used in Fico Scores are: payment history (35%), amounts owed (30%), length of credit history (15%), new credit (10%) and credit mix (10%) <https://www.myfico.com/credit-education/whats-in-your-credit-score>

instilled in Americans by their parents (Krabbe 2020). For example, Ellen⁶ is a white American woman, currently studying social sciences at a university in Lithuania, whose parents wanted to ‘build’ her credit while she was still a student. Her parents had already saved up for Ellen’s tuition expenses, but they nevertheless had Ellen take out student loans. Her parents sought to help Ellen create a good credit score by meeting each repayment instalment successfully, and she perceived the loans as her ‘beginning credit’. While taking out student loans does not require the individual to have a FICO Score, paying the loans off may contribute positively towards one’s credit score and thereby improve one’s future loan conditions when one wants to purchase a car or a home.⁷ Since the 1990s, credit scoring has become part of public consciousness, and today it plays a role in several other domains. Some dating websites match people based on their scores and revealing each other’s credit scores is a common practice among potential romantic partners (Gusterson 2019). Some landlords make rental decisions based on the rental applicant’s credit scores, while credit checks of potential employees are widely used by Human Resources Departments in those states that have not yet banned this practice (Ballance et al. 2020; O’Neil 2016, 147; Hurley and Adebayo 2017, 154,148).

From Individual Summaries to Statistical Approximations

Early commercial reporting firms invented a method to convert an individual’s reputation into a summary of their creditworthiness, and, in the process, they created a new type of commodity: personal information. To complete such a summary of creditworthiness, an extensive collection of certain types of information was deemed necessary, including health data, legal and criminal history, job performance and domestic arrangements (Lauer 2017). The information collected was so comprehensive that during the early twentieth century, the Federal Bureau of Investigation and the International Revenue Service needed to rely on the credit bureaus to obtain information about suspected criminals or tax-evaders (Lauer 2017). When the wider public became aware of these credit reporting practices, the outcry forced Congress to pass the 1970 Fair Credit Reporting Act (FCRA), which opened credit bureaus’ files to scrutiny and allowed citizens to challenge and correct their credit information (Pasquale 2015). While credit reports became more transparent due to the FCRA, the actual credit scores remained opaque mathematical calculations (Pasquale 2015). Four years later, the Equal Credit Opportunity Act (ECOA) was passed, prohibiting the linking of individual’s social characteristics to their creditworthiness, e.g., their race, gender, national origin, marital status, and religion (Marron 2009). However, over time and with the rise of algorithms, the calculation of credit scores is no longer based on individual borrowers. Instead, sophisticated predictive models and algorithms are used that pool together

⁶ Pseudonym used to protect the identity of the interlocutor interviewed in 2018.

⁷ <https://www.experian.com/blogs/ask-experian/do-student-loans-help-build-credit/>

individuals and score them based on a set of numerical and calculable factors (Lauer 2017; O’Neil 2016).

Creditworthiness by Association

In combination with the aforementioned development, the entire credit-scoring industry has moved towards the use of less conventional data for assessing an individual’s level of creditworthiness. For example, in 2016, FICO introduced the FICO Score XD in collaboration with the credit bureau Equifax and the risk management company LexisNexis Risk Solutions. The purpose of Score XD was to assess the creditworthiness of consumers who ‘cannot be scored appropriately, either due to insufficient or stale data in traditional credit bureau files’ (2019 Fair Isaac Corporation). The FICO Score XD is calculated through what FICO itself denotes as ‘alternative data sources’, including mobile phone payments, public records and property data, although the weight of each of these data sources is not disclosed. FICO markets its FICO Score XD to potential lender clients (referred to as ‘distribution partners’) as a way for them to extend their ‘scorable universe by millions of consumers,’ and ‘safely extend credit to a largely untapped market’ (2019 Fair Isaac Corporation, 4168PS 07/19 PDF).⁸ In 2019, and in partnership with the companies Experian and Finicity, FICO launched the pilot phase of the UltraFICO Score. UltraFICO ‘can unlock more credit opportunities for millions of hardworking people’ by including in its assessment consumers’ banking activity, such as account balance and frequency of transactions (Hiller and Jones 2021).⁹ As consumer credit is a necessity for most Americans, the increasing use of ‘alternative data sources’ may provide some opportunities for consumers with no credit history; by handing over one’s personal data to the credit scoring firm, the individual can overcome the familiar Catch-22 dilemma: to qualify for a loan, one must have a credit history, but to have a credit history one must have had loans. Even though the credit-scoring industry is dominated by FICO, the increasing use of ‘alterative data sources’ is largely driven by start-ups challenging the status-quo and operating by the logic of ‘all data is credit data.’ They promise better results in assessing the ‘thin file’ borrowers who lack conventional indicators of creditworthiness, for example by having no to little credit history (Hurley and Adebayo 2017, 148, 156). Examples of alternative data considered for these new forms of credit assessment include consumers’ friends and neighbours, their socio-economic background, hobbies and other ‘fringe data’ that one usually does not think of as being linked to creditworthiness (O’Neil 2016; Hiller and Jones 2021; Hurley and Adebayo 2017, 151, 158). For example, attending marriage counselling can negatively affect one’s credit score. Statistically, marriage counselling is correlated with marital discord, which can lead to financial distress in the household (Pasquale 2015). Hence, using such ‘fringe data’, companies draw a behavioural profile of consumers enabling them to evaluate their trustworthiness in real time and in the future. A similar predictive logic is

⁸ <https://www.fico.com/en/resource-access/download/4045>

⁹ <https://www.fico.com/ultrafico/>

found in other fields such as policing, where large-scale data sets include not just correlation between the time or place when a given crime was committed, but also other data such as the weather or sport events. All this data is used to predict where a crime will occur and dispatch officers in advance (Kaufmann et al. 2019). The combination of ‘fringe data’ and algorithmic predictions has been termed ‘creditworthiness by association’ or proxies by Hurley and Ardebayo (2017). The term refers to behavioural scoring where consumers’ familial, religious, social, or other affiliations determine the eligibility for a loan. Hurley and Ardebayo provide an account of an Afro-American Atlanta businessman Kevin Johnson, who despite of having maintained his credit score since college, had his credit lowered by almost two-thirds due to ‘[o]ther customers who ha[d] used their card at establishments where [Kevin] recently shopped have a poor repayment history with American Express’ (Hurley and Adebayo 2015, 150-151). Stories like this, demonstrate how classifying people may exacerbate existing biases and penalize consumers for carrying out activities that are associated with specific socio-economic groups (Fourcade and Healy 2013; Hurley and Adebayo 2015). A recent competitor in the credit-scoring industry is the start-up Zest AI, previously known as ZestFinance (Hurley and Adebayo 2015; O’Neil 2016). The company’s data collection approach is based on four categories: 1) borrowers’ data, 2) proprietary data, 3) public data and 4) social network data. Zest AI’s algorithm patent application, filed in 2014, provides some additional insight into how the algorithm works. For example, the speed with which a loan applicant scrolls through an online ‘Terms and Conditions’ disclosure at ZestFinance’s pay-day loan affiliate ZestCash website is considered an indicator of an applicant’s responsibility – the higher the speed, the lower the score (Hurley and Adebayo 2015). The company also uses punctuation and spelling mistakes as proxies for ‘lower level of education’ (O’Neil 2016). The example of ZestFinance illustrates how companies attempt to predict credit risk by using data points with no individual assessment of financial creditworthiness. In addition, due to their complexity and their proprietary character, the algorithms that determine the credit scores are not always clear for lenders (Jones and Hiller 2021:15). This development has not gone unnoticed by legislators; in July 2019, the US House of Representatives held a hearing on the use of alternative data in underwriting practices as well as credit scoring.¹⁰ Despite the growing awareness, legislation has not prevented the development of a credit data market surveilling citizens and reselling data.

The US Credit Scoring Model

The US credit scoring model has become an influential governmental regime that permeates everyday life for Americans, who are increasingly pushed to take an entrepreneurial interest in cultivating and monitoring their creditworthiness (Martin 2001). Credit scoring actively shapes Americans’ subjectivities and structures their opportunities and life-chances.

¹⁰ <https://www.congress.gov/event/116th-congress/house-event/LC65599/text?s=1&r=3>

Whereas earlier surveillance and evaluation in the US required an assessment of an individual's credit history, today's algorithmic credit scoring is based on social profiling, what Hurley and Ardebayo (2017) term 'scoring by association'. An individual's credit score is less a reflection of their *actual* financial behaviour, even if it has pretensions of portraying individual credit risk with greater accuracy than previous scoring models. This shift from individual to associational models entails a change in business models. An individual's 'creditworthiness' is furthermore no longer just a matter of whether they should be granted a loan. Credit evaluation becomes a calculation of *possible* profit generation rather than an estimation of a *probability* of default (see also Adkins 2017). A credit score is no longer just a risk assessment, it is a value assessment in a commercial sense. The general development towards algorithmic governance in the realm of credit is therefore also an expression of how financial capitalism has evolved into securitized credit/debt products (Ho 2009; Luyendijk 2018). An individual's credit score is a product that can be sold to third party companies. The basis of credit scoring in the US has developed from a collection of individually based assessments based on past behaviour to a collection of statistical predictive calculations based on behaviour by associated groups. The US credit scoring model rests on and promotes the capitalization of personal data in growing data markets by an industry of data brokers.

Credit Scoring in Denmark

In Denmark, formal credit scoring has a brief history and has taken a rather different route compared to the United States. The Danish credit assessment model has traditionally been 'negative', in the sense that it has focused on identifying potential defaulters rather than on evaluating the financial potential of all consumers, as in the US. It is essentially a 'blacklist' of delinquent borrowers – a list which one can exit if one's bad debt situation is resolved (Jørgensen 2014). The main Danish credit registry firm is Experian (formerly known as RKI, Ribers), which registers defaulters (up to five years).¹¹ Danish banks and private companies access the default register when deciding whether to provide a consumer loan, mortgage or credit line to customers. This scoring model, therefore, categorizes consumers in two groups: those who are likely to default and those who are not. The main credit-providing and credit-assessment institutions are the Danish banks, which have traditionally been responsible for providing credit to private households (Statistics Denmark 2019). In recent years, branches of global credit bureaus and finance companies have arrived at the Danish market. The finance companies provide (high interest) consumer loans, often called 'quick loans', to low-income customers or to those who do not want to go through bank channels (Kongerne af Kviklån 2019; Betalingsrådet 2015). These finance companies are subject to consumer law, but not to the same public regulation as Danish banks. However, all professional lenders are obliged to assess consumer's creditworthiness. Credit evaluation of consumers is regulated by

¹¹ After five years, one is deleted from the register regardless of whether the debt has been paid.

Danish credit legislation¹² (Jørgensen 2015) and by consumer privacy laws, mainly the GDPR (Directive 95/46/EC). One consequence of these consumer privacy laws is that banks cannot sell or share information about customers with other financial institutions, nor do they have full access to information about their customers' possible debt to other banks/credit institutions or to other lenders. Due to GDPR, although credit decisions may be decided based on various algorithmic processes, customers have the right to request a manual description of the reasons behind a credit decision, e.g., a loan rejection (European Data Protection Board 2019).

Profiling and Automatic Credit Scoring by Danish banks

Profiling is a form of automated processing of your personal data to evaluate certain personal aspects relating to you to analyse or predict aspects concerning, for example, your economic situation, personal preferences, interests, reliability, behaviour, location or movements (Danske Bank A/S Privacy Notice 2020).

Despite the general negative scoring model and the tight regulation, however, Danish banks have developed a pervasive system of automated scoring of their customers in recent years. As the quote from Danske Bank's privacy policy above shows, scoring includes a broad range of personal data, including *geographical movements, behaviour, and personal preferences*. This development of individual credit scoring has taken place 'below the radar', and the actual credit score is not formally available to customers.¹³ Public news media have expressed only limited interest in the Danish evaluation system, and the topic of credit scoring has only received public attention because of controversies over presumably *inadequate* credit scoring systems used by the growing industry of private lenders that offer high interest loans to financially vulnerable citizens (Jørgensen 2014; Hohnen 2020). According to one of the few articles on the topic of credit scoring in Denmark, systematic and algorithmic risk assessment developed around the millennium (Alhøj 2001). A recent interview with an employee in a large Danish bank confirms that algorithmic scoring models have grown rapidly and that Danish banks now calculate credit scores for all their customers.

If you apply for a loan and if you have been a customer of ours for several years, then we use what we call 'an application score'. This is based partly on a 'behaviour score' building on our knowledge about you. We calculate such a score for all our

¹² As specified in Article 8 of the Consumer Credit Directive (2008) and in The Consumer Credit Agreement Act, section 7c (2010)

¹³ One of the authors contacted her bank and asked to know her credit score. However, this information was denied by the bank as her individual credit score was categorised as 'a business secret'.

customers once a month... the scores are calculated mathematically, we use some data mining and forecasting ('Jan', employee in a large Danish Bank).

According to Jan, credit scoring of customers by Danish banks is carried out on a regular basis, focusing mainly on the customer's financial behaviour and credit trajectories, with data harvested primarily from the customers' digital interactions with the bank, for instance when accessing 'Netbank' or writing to bank advisors. Data tracking is therefore based largely on consumers' behaviour when resolving their finances digitally. Because of the widespread usage of Danish debit and credit cards, which are issued by banks, banks also have an enormous dataset of customers' daily consumption patterns (Boye 2017). These consumer data, however, may not legally be used in credit scoring. The ways these types of data are used and how data points are combined in algorithms calculating credit scores, however, are regarded as complex mathematics and/or as business secrets and are thus not publicly accessible (*ibid.*).

According to Alhøj (2001), Danish banks use various forms of automated scoring. For new customers, i.e., those applying for a loan or credit line, a general application-scoring model is used. In that case, the potential borrower is asked a limited number of questions concerning their financial situation which are then fed into a data model. The applicant must also provide the bank with additional information, typically total income, taxes paid, accounts held abroad, foreign debt, etc. For existing customers, the banks have developed a behaviour-scoring algorithm based on their past financial behaviour. Behaviour-scoring has been applied for years by Danish banks (Alhøj 2001). Behaviour scoring uses unstructured data from e-mail correspondence and logged customer calls that machine learning technology can harvest and use for further analysis (Boye 2017). Behavioural data harvested internally, via the customer's behaviour may include, for instance, the time of day when they access their bank accounts or when an application for a loan has been submitted, as well as other details in the digital behaviour when managing one's finances, including checking for possible overdraft.

As mentioned above, Danish and EU legislation regulates what kinds of data may be included in their credit scoring. Mining from social media, for example, is only allowed to be used for marketing purposes, and most banks have even been reluctant to include such data, because they fear adverse customer responses (Olsen 2016). In contrast to the US, Danish banks have until recently been prohibited from collecting external personal data and they are also not allowed to sell personal information used for credit scoring to third parties (Directive 95/46/EC/GDPR, European Data Protection Board 2019). Recent legislation on what is

referred to as PSD2¹⁴ however, has opened new data tracking possibilities for the banks, which can now include automated analysis of consumer patterns in their marketing activities although still not in assessing customer creditworthiness (Boye, 2017).

An increasing number of private lending companies, fintech start-ups and credit data companies have also emerged on the Danish credit market, carrying out their own form of credit scoring. For one, the US-based credit scoring company, Experian, has recently established themselves in Denmark. In addition to purchasing the former RKI registry of default debtors, Experian has established a database of Danish credit customers and a network for financial companies seeking credit information. The network brings together several of the finance companies offering payday loans to individuals. These private lending companies have a wider legal space of operation when it comes to the harvesting of personal data. They are subject to consumer law, but not to the same kind of regulatory measures which govern the banking sector (Jørgensen 2015). Although, their scoring models include data based on profiling (dividing customers into statistical segments), they are not allowed to use this aggregated information as the sole basis for credit scoring/credit decisions (European Data Protection Board 2019). As mentioned above, lending companies' credit scoring practices have received public criticism due to their high interest rates and late fees and their business models, which primarily target the most financially vulnerable consumers (Jørgensen 2015).

In Denmark, both the regular credit scoring, the harvesting of behavioural data and the use of algorithmic credit scoring models have remained largely invisible to Danish consumers. There have been a few magazine articles with titles such as: 'Your Bank Knows More about You Than Ever Before (and Wants to Know Much More)' (Boye 2017) and 'the Banks Follow You on the Internet' (Olsen 2016). However, these have not sparked any wider political or public debate.

I don't think the average Dane has any idea of the kinds of information that is being harvested about them. Nor of what their bank or insurance company can use it for. The extent of information collection and the opacity that characterizes this development is really a problem (Jesper Lund, chair of IT-Political Association of Denmark, quoted in Version2, 2017, our translation).

¹⁴ In September 2019, a new Payment Service Directive 2 (PSD2) took effect which has the potential to fundamentally alter the previous system. PSD2 is designed to force providers of payment services (banks) to improve customer authentication processes and to bring in new regulation related to third-party involvement.

The Danish Credit Scoring Model

The Danish usage of algorithmic credit scoring differs from that of the US in several ways. Denmark did not experience a historical development of a credit scoring industry, and the arrival of the US-based credit bureau Experian is very recent. Danish banks and financial institutions are limited by regulations, particularly the EU GDPR, which protects credit data, and by other EU regulation that prohibits credit evaluation based solely on data that cannot be identified as directly economically relevant. In recent decades, however, an elaborate system of credit scoring has ‘slipped in’ to Danish life without any public debate. This insertion of a credit scoring regime is now operating (in different ways) under the guise of different creditors. In addition, Experian, which focuses on selling risk scoring and marketing of data, has now established a network of financial companies who are sharing credit data. We thus see the development of algorithmic-based credit scoring manifesting itself differently in banks compared with other financial companies. In both these domains, we see a development of data-based surveillance and profiling of customers based on their behavioural data. In addition, we can observe a gradual development towards the inclusion of non-financial data in credit scoring such as data harvested from social media. Such data are already part of the scoring models used by financial companies, as these firms have hitherto not been as tightly regulated in terms of harvesting of personal data as the banks. Nevertheless, Danish Banks have also started collecting non-financial data using data harvesting from social media. These data are used mainly for marketing of financial products to individual customers; hence social media tracking is not (yet) used by banks in their credit scoring.

Where the US seems to have three giant firms dominating the credit scoring arena and to some extent following one standardized scoring system, the Danish credit scoring model appears more ‘compartmentalized’ and fragmented, with various institutions creating their own distinct scoring systems. Although Danish banks have a limited ‘space of operation’ when it comes to the mining, selling, and usage of personal data in credit assessment, they have developed models for algorithmic credit scoring and behavioural predictions based on surveillance and profiling of their own customers. Predictions are limited to banking decisions, and until recently, data and predictions have been kept within the bank and thus not resold (see note on PSD2 above). However, the regular credit scoring based on behavioural data remains unknown to most bank customers. This has created a peculiar combination of *openness and opacity* in Danish credit scoring. The openness is related to the GDPR, which entitles consumers to know their own credit scores, while opacity is reflected in the fact that the very existence of the scoring system remains hidden. Moreover, the increasing surveillance of bank customers’ digital behaviour in their communications with their bank has gone largely unnoticed in the public debate. The Danish credit scoring model is equally *intense and confined*. While banks are limited in sharing and reselling personal credit data to other industries like employers or insurance firms, algorithmic-based credit scoring, nevertheless, is pervasive. The Danish case can thus be conceived as a kind of ‘silo-surveillance’, where behavioural data, profiling and automated scoring form

the basis of the calculation of the individual credit score. Although GDPR ensures individuals the right to demand an explanation of concrete credit evaluations, for example in case of a rejection of credit, the existence of the automated evaluation system that operates in banks' calculations of interest rates or other conditions remains unknown to the customers. While EU data regulations are often promoted as 'a solution' to surveillance in the Danish case, the case of credit scoring shows how GDPR (and expected protection of privacy) has promoted the development of a particular form of surveillance and prediction of individual financial behaviour, which is then used in profiling and automated credit scoring.

From Credit Scoring to Algorithmic Governance

How does the analysis of credit scoring contribute to an analytical understanding of algorithmic governance studies and what conceptual issues can be highlighted based on the comparison of credit scoring configurations in the US and Denmark? In the following, we pinpoint what we see as key analytical issues of relevance to the anthropological field of algorithmic governance.

Credit evaluation has a long history. In addition, the credit evaluation industry has been at the forefront of developments in algorithmic prediction products, both in terms of profiling and credit prediction and in expanding business models, for instance by combining credit evaluation with marketing. Credit evaluation has historically been based on the surveillance and the moral and social judgments of individual citizens; close surveillance of individual citizens is nothing new. Rather, the recent innovation in credit scoring seems to lie in the combination of an increasing utilization of algorithmic predictions and a wider usage of profiling based on behavioural data and/or 'credit evaluation by association' – understood here as 'personalized' credit trajectories based on the behaviour of others – in the credit scoring of individuals.

In addition, the development of increasing data-based surveillance exemplifies how the purpose of credit scoring has been reoriented: the evaluation of risk has led to the harvesting of personal data for marketing purposes or sale of our credit behaviours to money lenders and other firms. Our creditworthiness is now a product that can be packaged and sold. This paradigmatic shift is related to broader market changes and forms of political regulation as well as to technical developments in the use of big data and algorithmic predictions. Following Shoshana Zuboff's call for action (2019), we need more scholarly inquiry as well popular debate on the way in which algorithmic predictions and behavioural real time nudging may restrict consumers' and citizens' power to decide over their own futures. Based on the empirical analysis above, however, we suggest that it is not only the 'future tense' that is at stake here. Developments in credit scoring highlight the significant 'recasting' of past consumer behaviour which is used as the basis for predictive assessments. Whereas earlier credit scoring was based on *personal* credit trajectories, current credit scoring is moving in the direction of not only relying on aggregated data, but on the aggregation of a range of opaque

data, which is then compiled into a score of an individual's personal creditworthiness. The assessment of creditworthiness individuals' personal credit history – the money they borrowed and things they purchased – turns into a constructed personification of an aggregation of data traces harvested based on present digital behaviour (the Danish case) or others' financial history (the US case). In both cases, the personal credit score is not only less personal than what is suggested, but it also creates a new notion of what is meant by 'past' financial behaviour. This automated 'past' becomes a representation of individual morality and reliability, forming an entirely new basis for calculating the individual's future financial conduct. While credit scores based on big data are presented as an assessment of *personal* creditworthiness, the scores have de facto become *detached* from the financial history and moral conduct of the individual. In the field of credit scoring, we see a new combination of close surveillance of personal behaviour that is now *assumed to* be related to creditworthiness and surveillance of data traces and contexts merely *associated* with the individual. This usage of aggregate data is different from more traditional statistics by letting aggregations *perform* as assessments of personal morality and character.

The way algorithmic predictions are being used in the assessment of creditworthiness shows that credit scoring has moved away from a focus on individuals' credit histories towards increasing use of behavioural and associated data in both the US and Denmark. The juxtaposition of the two cases also shows how political and legal contexts have shaped the configuration of algorithmic models and how different social and political issues of concern are raised in each case.

In the US, the field of credit scoring has developed into a multi-levelled industry, which includes both the existing evaluation firms, new financial start-ups, providing 'thin file scores', and an industry of data brokers. Furthermore, the lack of legal protection of private data has facilitated a growing dissemination of both the personal data involved in constructing credit scores and the scores themselves across industries and domains. The deregulated market for data has created a situation where automated credit scores diffuse to ever more domains of everyday life, affecting people's access to education, housing and employment. However, the fact that the impact of credit scores is widely known has resulted in public debate including recent hearings in the US Congress and a growing critique in the academic and popular literature. These public concerns, however, focus on the potential 'flaws' of the system in terms of bias and possible mistakes. Criticisms of credit scoring include stories about discriminatory practices, mistaken identification and name confusion resulting in misplaced scores, or cases experienced as 'unfair treatment'. Overlooked in these debates has been the very logics of the automated system and the way these logics reconfigure the notion of an 'individual creditworthiness'. Because the legitimacy of this 'approximation' system has not been questioned, its existence and dissemination has led credit scores to have an increasing impact on various domains of social life. One's credit score becomes an identity, or in some cases a stigma that cannot be expunged.

The Danish context, although formally characterized by a high degree of consumer protection and restrictions on data brokering, reveals a similar development towards the inclusion of aggregated personal data, increased surveillance of digital behaviour (both financial and non-financial), and the presentation of personified data as a more accurate evaluation of individual character than previous credit evaluation. However, while The European Union's General Data Protection Regulation has imposed restrictions on the dissemination of Danish credit data and credit scores, the level of protection offered is in our view overestimated. In the introduction to *Life by Algorithms*, Hugh Gusterson highlights GDPR as a way of diminishing the influence of what he terms 'roboprocesses' of data (Gusterson 2019: 12). However, while the analysis of the Danish credit scoring regime confirms that GDPR has certainly limited the dissemination of personal credit data and of credit scores compared to the United States, the Danish case also reveals the development of an intense surveillance of customers by banks and financial start-ups. Moreover, the close surveillance and harvesting of behavioural data as well as the algorithm-based profiling has gone almost completely unnoticed by the wider Danish public. GDPR has *not* prevented intensive surveillance and 'credit scoring by approximation'. Instead, the belief in the power of privacy protection seems to have fuelled the development of a particular Danish credit scoring system characterized of *silo-surveillance* that has remained completely under the radar compared to the widespread scepticism, or even antipathy, to the credit scoring regime in the US.

Critical algorithm studies have raised a number of concerns related to how algorithms shape social life (Katzenbach and Ulrich 2019; Gusterson 2019). Several studies have focused on how automated calculations based on the harvesting and profiling of individual data traces have a social impact in terms of subjectivity, agency, social relations, and temporality (Amoore and Piotukh 2015). Other studies have emphasized power asymmetries, oppressive surveillance, and breaches of privacy (Larsson 2017; Zuboff 2019; O'Neil 2016). Finally, recent ethnographically inspired studies, focus on algorithms as cultural forms (Lange et al. 2019). In the analysis of credit scoring above, we have shown how algorithms shape sociality and temporality in significant ways and how credit assessments reconfigure behavioural data into personalized credit trajectories. While algorithmic credit scoring is becoming increasingly significant for peoples' everyday life, the types of data and predictions on which they rest are becoming increasingly *detached* from and *unavailable* to those who are being scored. The empirical analysis of algorithmic credit scoring models shows the need for an anthropological framework that integrates a focus on the governance of algorithms (including policy regime as well as market models) with the particular logics of algorithmic calculations. Such a framework has the potential to show how algorithmic governance shapes individuals' pasts and futures and to pinpoint general as well as specific policy areas of concern.

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