CREDIT SCORING IN THE ERA OF BIG DATA

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ABSTRACT

For most Americans, access to credit is an essential requirement for upward mobility and financial success. A favorable credit rating is necessary to purchase a home or car, to start a new business, to seek higher education, or to pursue other important goals. For many consumers, strong credit is also necessary to gain access to employment, rental housing, and essential services such as insurance. At present, however, individuals have very little control over how they are scored and have even less ability to contest inaccurate, biased, or unfair assessments of their credit. Traditional, automated credit-scoring tools raise longstanding concerns of accuracy and unfairness. The recent advent of new "big-data" credit-scoring products heightens these concerns.

The credit-scoring industry has experienced a recent explosion of start-ups that take an "all data is credit data" approach, combining conventional credit information with thousands of data points mined from consumers' offline and online activities. Big-data scoring tools may now base credit decisions on where people shop, the purchases they make, their online social media networks, and various other factors that are not intuitively related to creditworthiness. While the details of many of these products remain closely guarded trade secrets, the proponents of big-data credit scoring argue that these tools can reach millions of underserved consumers by using complex algorithms to detect patterns and signals within a vast sea of information. While alternative credit scoring may ultimately benefit some consumers, it also poses significant risks.

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Credit-scoring tools that integrate thousands of data points, most of which are collected without consumer knowledge, create serious problems of transparency. Consumers have limited ability to identify and contest unfair credit decisions, and little chance to understand what steps they should take to improve their credit. Recent studies have also questioned the accuracy of the data used by these tools, in some cases identifying serious flaws that have a substantial bearing on lending decisions. Big-data tools may also risk creating a system of "creditworthiness by association" in which consumers' familial, religious, social, and other affiliations determine their eligibility for an affordable loan. These tools may furthermore obscure discriminatory and subjective lending policies behind a single "objective" score. Such discriminatory scoring may not be intentional; instead, sophisticated algorithms may combine facially neutral data points and treat them as proxies for immutable characteristics such as race or gender, thereby circumventing existing non-discrimination laws and systematically denying credit access to certain groups. Finally, big-data tools may allow online payday lenders to target the most vulnerable consumers and lure them into debt traps.

Existing laws are insufficient to respond to the challenges posed by credit scoring in the era of big-data. While federal law prohibits certain forms of discrimination in lending and ensures that consumers have limited rights to review and correct errors in their credit reports, these laws do not go far enough to make sure that credit-scoring systems are accurate, transparent, and unbiased. Existing laws also do little to prevent the use of predatory scoring techniques that may be geared to target vulnerable consumers with usurious loans.

This article, which has been developed as part of a collaborative effort between lawyers and data scientists, explores the problems posed by big-data credit-scoring tools and analyzes the gaps in existing laws. It also sets out a framework for comprehensive legislative change, proposing concrete solutions that would promote innovation while holding developers and users of credit-scoring tools to high standards of accuracy, transparency, fairness, and non-discrimination.

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I.   INTRODUCTION

One day in late 2008, Atlanta businessman Kevin Johnson returned home from his vacation to find an unpleasant surprise waiting in his mailbox. It was a letter from his credit card company, American Express, informing him that his credit limit had been lowered from $10,800 to a mere $3,800.[1] While Kevin was shocked that American Express would make such a drastic change to his limit, he was even more surprised by the company's reasoning. By any measure, Kevin had been an ideal customer. Kevin, who is black, was running a successful Atlanta public relations firm, was a homeowner, and had always paid his bills on time, rarely carrying a balance on his card.[2] Kevin's father, who had worked in the credit industry, had taught him the importance of responsible spending and, "because of his father's lessons,

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[1] Ron Lieber, *American Express Kept a (Very) Watchful Eye on Charges*, N.Y. TIMES (Jan. 30, 2009), http://www.nytimes.com/2009/01/31/your-money/credit-and-debit-cards/31money.html?pagewanted=all [https://perma.cc/QQ7P-7QHP].

[2] Chris Cuomo et al., *'GMA' Gets Answers: Some Credit Card Companies Financially Profiling Customers*, ABC NEWS (Jan. 28, 2009), http://abcnews.go.com/GMA/TheLaw/gma-answers-credit-card-companies-financially-profiling-customers/story?id=6747461&singlePage=true [https://perma.cc/J4SA-N2ZR].

[Kevin had] scrupulously maintained his credit since college."[3] Yet his stellar track record and efforts to maintain "scrupulous" credit seemed to matter little, if at all, to American Express. The company had deemed him a risk simply because, as the letter put it, "[o]ther customers who ha[d] used their card at establishments where [Kevin] recently shopped have a poor repayment history with American Express."[4] When Kevin sought an explanation, the company was unwilling to share any information on which of businesses – many of them major retailers – contributed to American Express's decision to slash Kevin's limit by more than 65 percent.[5]

Kevin Johnson was an early victim of a new form of credit assessment that some experts have labeled "behavioral analysis" or "behavioral scoring,"[6] but which might also be described as "creditworthiness by association." Rather than being judged on their individual merits and actions, consumers may find that access to credit depends on a lender's opaque predictions about a consumer's friends, neighbors, and people with similar interests, income levels, and backgrounds. This data-centric approach to credit is reminiscent of the racially discriminatory and now illegal practice of "redlining," by which lenders classified applicants on the basis their zip codes, and not their individual capacities to borrow responsibly.[7]

Since 2008, lenders have only intensified their use of big-data profiling techniques. With increased use of smartphones, social media, and electronic means of payment, every consumer leaves behind a digital trail of data that companies – including lenders and credit scorers – are eagerly scooping up and analyzing as a means to better predict consumer behavior.[8] The credit-scoring industry has experienced a recent explosion of start-ups that take an "all data is credit data" approach that combines conventional credit information with thousands of data points mined from consumers' offline and online activities.[9] Many companies also use complex algorithms to detect patterns and signals within a

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3   *Id.*
4   Lieber, *supra* note 1.
5   Cuomo et al., *supra* note 2.
6   *See, e.g., id.* (quoting Robert Manning).
7   Tracy Alloway, *Big data: Credit where credit's due*, FINANCIAL TIMES (Feb. 4, 2015),   http://www.ft.com/cms/s/0/7933792e-a2e6-11e4-9c06-00144feab7de.html [https://perma.cc/7D8J-JHWY].
8   Natasha Singer, *Mapping, and Sharing, the Consumer Genome*, N.Y. TIMES (June 16, 2012), http://www.nytimes.com/2012/06/17/technology/acxiom-the-quiet-giant-of-consumer-database-marketing.html?pagewanted=all&_r=0 [https://perma.cc/EW2X-HALB].
9   *See, e.g.*, ZestFinance, *Our Story*, http://www.zestfinance.com/our-story.html [https://perma.cc/DBS8-R34M].

vast sea of information about consumers' daily lives.[10] Forecasting credit risk on the basis of a consumer's retail preferences is just the tip of the iceberg; many alternative credit-assessment tools now claim to analyze everything from consumer browsing habits and social media activities to geolocation data.[11]

While proponents of big-data credit analysis claim that these new analytical tools could revolutionize the lending industry and ultimately benefit consumers, experiences like Kevin Johnson's are a harbinger of the hazards. For the majority of Americans, fair access to credit can be a make-or-break determinant of whether a person can buy a home, own a car, or get a college education. The use of non-transparent credit-assessment systems that judge consumers based on factors that they are not aware of and which may be beyond consumers' control, fundamentally conflicts with the American ideal of self-determination. As one critic put it, a consumer "can get in a death spiral simply by making one wrong move, when algorithms amplify a bad data point and cause cascading effects."[12] This risk is all the more troubling when consumers have no way of distinguishing the "right moves" from the "wrong" ones. Unless the rules of the credit system are transparent and predictable, access to the American dream may turn upon arbitrary factors rather than merit.

Big-data assessment tools also have "the potential to eclipse longstanding civil rights protections in how personal information is used in [the] . . . . . . marketplace,"[13] by using seemingly innocuous information, like consumers' retail preferences, as proxies for sensitive attributes like race. Kevin Johnson's story raises the troubling possibility that consumers might be penalized for activities that are associated with particular racial, ethnic, or socioeconomic groups. Rather than fostering change for the good, big-data credit-assessment tools may only shield and exacerbate preexisting forms of bias.

Finally, these new tools hold the risk that even the most careful consumers could fall victim to flawed or inaccurate data. The problem of inaccuracy has long proved a challenge

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[10] *See* PERSIS YU ET AL., BIG DATA: A BIG DISAPPOINTMENT FOR SCORING CONSUMER CREDIT RISK, NAT'L CONSUMER LAW CTR. 10 (Mar. 2014), http://www.nclc.org/issues/big-data.html [https://perma.cc/8P4X-R2UK].

[11] *See* Robinson + Yu, *Knowing the Score: New Data, Underwriting, and Marketing in the Consumer Credit Marketplace* 15 (Oct. 29, 2014), http://www.robinsonyu.com/pdfs/Knowing_the_Score_Oct_2014_v1_1.pdf [https://perma.cc/C5PJ-3H3G].

[12] Alloway, *supra* note 7 (quoting Frank Pasquale).

[13] EXEC. OFFICE OF THE PRESIDENT, BIG DATA: SEIZING OPPORTUNITIES, PRESERVING VALUES (May 2014), https://www.whitehouse.gov/sites/default/files/docs/big_data_privacy_report_may_1_2014.pdf [https://perma.cc/JA3C-93AA].

for traditional credit-scoring systems, which utilize a relatively limited set of data points.[14] Big-data credit-assessment tools are likely to compound this problem.[15] Everyone with a Netflix or Pandora account has witnessed firsthand how "smart" algorithms can draw poor inferences about users' preferences on the basis of a few atypical searches and stray clicks. There is mounting evidence that big-data credit-scoring systems, which employ thousands of data points that are surreptitiously and continuously mined from a consumer's offline and online activities, may incorporate a high degree of inaccurate information.[16] For example, a recent report indicates mobile location data can be particularly prone to inaccuracy.[17] While consumers have a legal right to correct inaccuracies in their credit reports, this may be practically impossible with big-data tools.

   This paper discusses how big-data tools are transforming the credit-scoring industry and the major risks and challenges these new tools pose. We compare traditional, automated scoring tools to emerging, big-data tools, and also provide an introduction to the terminology and concepts that are necessary to understand how big-data scoring works in practice. We describe the major steps that a credit scorer might follow to design and deploy a big-data scoring model, as well as the risks to consumers at every step in the process. Finally, we address gaps in the existing legal framework and propose a legislative solution that balances innovation with the need to preserve fairness, accuracy, and transparency in credit scoring.

II. TRADITIONAL CREDIT-ASSESSMENT TOOLS

   A credit score is a "summary of a person's apparent creditworthiness that is used to make underwriting decisions,"

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[14] *See* FED. TRADE COMM'N, REPORT TO CONGRESS UNDER SECTION 319 OF THE FAIR AND ACCURATE CREDIT TRANSACTIONS ACT OF 2003 (Dec. 2012), https://www.ftc.gov/sites/default/files/documents/reports/section-319-fair-and-accurate-credit-transactions-act-2003-fifth-interim-federal-trade-commission/130211factareport.pdf [https://perma.cc/MEY5-ZZ9K].

[15] *See* Brief for Center for Digital Democracy as Amici Curiae Supporting Respondents, Spokeo, Inc. v. Robins, No. 13-1339 (U.S.argued Nov. 2, 2015), 2015 WL 5302538, at *12-13.

[16] *See, e.g., id.*; *New Experian Data Quality Research Shows Inaccurate Data Preventing Desired Customer Insight*, EXPERIAN (Jan. 28, 2015), https://www.experianplc.com/media/news/2015/new-experian-data-quality-research-shows-inaccurate-data-preventing-desired-customer-insight [https://perma.cc/K6TR-SG3D].

[17] *See, e.g.,* Steven Jacobs, *Report: More Than Half of Mobile Location Data is Inaccurate*, STREETFIGHT (May 14, 2015), http://streetfightmag.com/2015/05/14/report-more-than-half-of-mobile-location-data-is-inaccurate [https://perma.cc/43L2-4ULH].

as well as to "predict the relative likelihood of a negative financial event, such as a default on a credit obligation."[18] Over the course of the past three decades, automated credit-scoring systems like those developed by the Fair and Isaac Corporation (FICO) have become a fundamental determinant of fiscal success for the majority of Americans.[19] Without a sufficiently favorable score from a major credit bureau, a consumer likely cannot "buy a home, build a business, or send [her] children to college."[20] Credit scores and reports are not only used for lending decisions. Many employers review credit reports when determining whom to hire, or when deciding whether to promote an existing employee.[21] Landlords also commonly use credit reports to screen potential tenants.[22]

The mainstream credit-scoring market is generally segmented into consumer-reporting agencies, or "CRAs," and companies that develop and license automated scoring methodologies.[23] CRAs, including the "big three" nationwide credit bureaus – TransUnion, Experian, and Equifax[24] – obtain data relating to individual consumers and compile these data into what are commonly referred to as "credit reports." CRAs generally obtain the information that goes into credit reports from credit-information "furnishers" such as credit-card companies, mortgage lenders, and potentially other sources.[25] According to the Consumer Financial Protection Bureau (CFPB), each of the big-three CRAs receives approximately 1.3 billion updates for over 200 million consumer files each month.[26] The information that is compiled into credit reports is

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18   *See* Robinson + Yu, *supra* note 11, at 7.

19   *See* YU, *supra* note 10, at 27 (FICO first introduced its flagship score in 1981).

20   Ashoka, *Banking the Unbanked: A How-To*, FORBES (Jun. 14, 2013), http://www.forbes.com/sites/ashoka/2013/06/14/banking-the-unbanked-a-how-to [https://perma.cc/PD4J-VFDT].

21   *See* Amy Traub, *Discredited: How Employment Credit Checks Keep Qualified Workers out of A Job*, DEMOS 1 (Feb. 2013), http://www.demos.org/discredited-how-employment-credit-checks-keep-qualified-workers-out-job [https://perma.cc/82CK-ZGNG].

22   *See* FED. TRADE COMM'N, USING CONSUMER REPORTS: WHAT LANDLORDS NEED TO KNOW (Dec. 2001), https://www.ftc.gov/system/files/documents/plain-language/bus49-using-consumer-reports-what-landlords-need-know.pdf [https://perma.cc/X7UH-ZWUE].

23   NATIONAL CONSUMER LAW CENTER, FAIR CREDIT REPORTING § 1.2.2 (8th ed. 2013).

24   15 U.S.C. § 1681a(p) (CRAs operating on a "nationwide basis").

25   MAUREEN MAHONEY, ERRORS AND GOTCHAS: HOW CREDIT ERRORS AND UNRELIABLE CREDIT SCORES HURT CONSUMERS, CONSUMERS UNION 4-5 (Apr. 9, 2014), http://consumersunion.org/wp-content/uploads/2014/04/Errors-and-Gotchas-report.pdf [https://perma.cc/T5YJ-8Y4A].

26   CONSUMER FIN. PROT. BUREAU, KEY DIMENSIONS AND PROCESSES IN THE U.S. CREDIT REPORTING SYSTEM: A REVIEW OF HOW THE NATION'S LARGEST CREDIT BUREAUS MANAGE CONSUMER DATA 21 & n.54 (Dec. 2012),

then used to score individual consumers using proprietary scoring models. In the traditional credit-scoring market, there are two main developers of credit-scoring models and software, namely FICO, and VantageScore, which is a joint venture of the big-three credit-scoring companies.[27] These companies develop multiple models and products that are suited to meet the needs and information held by CRAs and lenders. FICO, for example, produces "numerous FICO scoring models that vary by version (e.g., newer and older models), by the nationwide CRA that sells the score to lenders, and by industry."[28] FICO remains the most prominent credit-modeling company. According to the CFPB, during 2010, over 90 percent of lenders used FICO scores to make lending decisions.[29]

Automated underwriting is a relatively recent innovation. Prior to the 1980s, most lending decisions were entrusted to individual loan officers and specialists who evaluated applicants on an individual basis.[30] These underwriting processes were not only labor-intensive, but could be influenced by personal bias. Automated scoring tools, like early iterations of the FICO score, which was not widely adopted until the early 1990s,[31] were viewed as better alternatives that could increase efficiency and avoid the most egregious forms of discrimination.[32]

Traditional automated scoring frameworks like the FICO score have not proved a panacea, however, and there is concern that these tools unjustifiably disadvantage certain borrowers. An astounding number of U.S. consumers – 64 million according to an Experian report – are currently classed as "unscorable," meaning that they cannot access traditional forms of credit.[33] These consumers may be "immigrants or recent college grads [with] little to no credit history," or "people who haven't had an active credit account for at least six

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http://files.consumerfinance.gov/f/201212_cfpb_credit-reporting-white-paper.pdf [https://perma.cc/8QTV-24V6].

27   NATIONAL CONSUMER LAW CENTER, FAIR CREDIT REPORTING §§ 1.2.2; 14.4.4 (8th ed. 2013).

28   CONSUMER FIN. PROTECTION BUREAU, ANALYSIS OF DIFFERENCES BETWEEN CONSUMER AND CREDITOR-PURCHASED CREDIT SCORES 3-4 (2012), http://files.consumerfinance.gov/f/201209_Analysis_Differences_Consumer_C redit.pdf [https://perma.cc/PK8K-AS9Y].

29   NATIONAL CONSUMER LAW CENTER, FAIR CREDIT REPORTING § 14.4.4 (8th ed. 2013).

30   Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 8-9 (2014).

31   *See* Robinson + Yu, *supra* note 11, at 27.

32   *See id.*

33   Blake Ellis, *Millions Without Credit Scores not so Risky After All*, CNN MONEY (Aug. 14, 2013), http://money.cnn.com/2013/08/14/pf/credit-scores [https://perma.cc/AA8Y-ZU3K].

months."[34] Because traditional credit-scoring models consider a relatively limited set of data points, they may not adequately predict the creditworthiness of many "thin-file" consumers.[35] The FICO score, for instance, principally looks at a consumer's payment history, the amounts she owes, the length of her credit history, new credit, and types of credit she uses,[36] while omitting factors such as employment history, salary, and other items that might suggest creditworthiness.[37] As a practical consequence, traditional credit-scoring tools may also perpetuate unfairness by denying certain groups favorable access to credit merely because they have been excluded from the credit market in the past.

The data considered in traditional credit-scoring mechanisms can also be inaccurate. A 2013 Federal Trade Commission (FTC) study found that twenty-six percent of the consumers surveyed had errors in their credit reports, and these mistakes were material for thirteen percent of consumers, potentially resulting in denials, higher rates of interest and other less-favorable terms.[38] These errors also disproportionately impacted individuals with lower levels of education.[39] Even when a consumer identifies an error, the problem can take a significant amount of time to be corrected, thereby limiting the consumer's ability to maintain good credit in the future.[40] In one particularly egregious example, CRA TransUnion repeatedly reported the bad debts of a woman named "Judith L. Upton," on the credit report corresponding to an entirely different individual, named "Judy Thomas."[41] After

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[34] *Id.*

[35] According to VantageScore, a major provider of credit-scoring tools, "not all of these consumers [currently classified as subprime borrowers] should be labeled subprime," and "more than 10 million of these consumers have either prime or near-prime credit scores" when additional information is taken into consideration. *See* VantageScore, *What lenders really think about unscorables* (July 2013), http://thescore.vantagescore.com/article/67 [https://perma.cc/A38N-F59E].

[36] *See* Robinson + Yu, *supra* note 11, at 9.

[37] *See FICO: What's not in my FICO scores*, MY FICO http://www.myfico.com/CreditEducation/WhatsNotInYourScore.aspx [https://perma.cc/3LUN-NRCD].

[38] Out of a survey population of 1,001 consumers. *See* FED. TRADE COMM'N, *supra* note 14, at i-iii.

[39] *See id.*, at 29.

[40] For example, in 2014, the Huffington Post reported on 69 year-old veteran who was forced out of his home as a result of an erroneously-reported debt on a credit card that he never held. The debt, which he disputed, remains on his credit score to this day. *See* Hunter Stuart, *It's Disturbing Likely that Your Credit Report is Wrong*, HUFFINGTON POST (Aug. 11, 2014), http://www.huffingtonpost.com/2014/08/11/credit-report-bureau-mistakes-_n_5661956.html [https://perma.cc/Q83N-3JBV].

[41] Rome Neal, *Mistaken Identity in Credit Report*, CBS NEWS (July 31, 2002), http://www.cbsnews.com/news/mistaken-identity-in-credit-report

extensive attempts to rectify the error, Ms. Thomas finally sued TransUnion, ultimately winning a multi-million dollar verdict.[42] Judy Thomas's experience is reflective of similar problems that other consumers have faced when they discover errors in their traditional credit reports.[43]

III. ALGORITHMS, MACHINE LEARNING, AND THE ALTERNATIVE CREDIT-SCORING MARKET

The perceived inability of traditional, automated credit scores to adequately capture "thin file" borrowers has prompted the emergence of alternative, big-data tools that promise lenders a way to "squeeze additional performance" out of their underwriting processes.[44] Although traditional factors, such as those used by FICO, remain central to contemporary lending decisions, the credit-scoring industry is witnessing a rapid shift to new, alternative tools. Even traditional credit-reporting and scoring agencies are developing alternative models that rely on non-traditional data. Experian, for instance, is already leveraging big data to develop "universal customer profiles" that integrate information from the online and offline activities

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[https://perma.cc/D9RQ-LUGR]. In addition to sharing similar first names, Ms. Thomas and Ms. Upton both had the same birth year, and had social security numbers that differed by one digit.

[42] *Id.*

[43] In 2013, a similar fate befell yet another, different Judy Thomas. According to a report by *60 Minutes*, Ohio resident Judy Thomas discovered that her credit reports inaccurately contained information on the debts of a Utah woman, Judy Kendall. As a result of the false information on her reports, Ms. Thomas struggled for years, unable to refinance her mortgage, obtain a new car, or even cosign for her children's student loans. *See 60 Minutes Report: 40 Million Mistakes: Is your credit report accurate?*, NAT'L ASS'N OF CONSUMER ADVOCATES, (Feb. 11, 2013), http://www.consumeradvocates.org/media/news/60-minutes-report-40-million-mistakes-your-credit-report-accurate [https://perma.cc/8YVD-5W4S] (transcript of *60 Minutes* report). Comedian John Oliver also recently took the big-three consumer reporting agencies to task for similarly egregious inaccuracies on various credit reports. In one example, a consumer's application to rent an apartment was denied because his credit report falsely identified him as a terrorist. In another example, an individual by the name of Samuel Jackson discovered that his credit report included information on three separate sex offenders who had shared his name. In yet another example, a Texas woman, discovered that credit reports from all three major agencies reported her as deceased. *See* Chris Lee, *HBO's John Oliver Shows the Infuriating Truth About Credit Reporting Agencies*, FORTUNE (Apr. 11, 2016), http://fortune.com/2016/04/11/hbo-john-oliver-reveals-the-awful-business-behind-credit-background-checks [https://perma.cc/T37G-PAQW].

[44] *See* Kevin Wack, *Evaluating the Viability of Alternative Credit Decisioning Tools: A $3.6 Billion Opportunity for the Auto- and Credit Card-Lending Markets*, AMERICAN BANKER (Jun. 20, 2013), http://www.lexisnexis.com/risk/downloads/whitepaper/alternative-credit-decisioning.pdf [https://perma.cc/HE7P-4NM8].

of thousands of consumers.[45] FICO has been testing out a new system that uses non-traditional data to assess thin-file borrowers; its new "FICO Score XD," which FICO developed in collaboration with the credit bureau Equifax, uses data on consumers' cable and cellphone accounts to predict creditworthiness.[46] While some of the data used in these alternative tools may seem logically related to a consumer's ability to manage a loan, for instance, utility bill payment histories,[47] other types of "fringe data" are increasingly employed, despite the lack of an intuitive link to creditworthiness.[48]

A number of emerging companies use proprietary "machine-learning" algorithms to sift and sort through thousands of data points available for each consumer. These companies treat their machine-learning tools as closely-guarded trade secrets, making it impossible to offer a comprehensive picture of the industry. However, some publicly-available information, particularly disclosures in patent applications, offers valuable insights into how machine-learning credit-scoring tools work and the risks that they may pose.

In this part, we provide an overview of the techniques and methodologies that big-data credit-scorers likely use to design, test, and deploy machine-learning tools to assess creditworthiness. We begin by introducing some basic terminology and concepts, and continue by describing how credit-scoring tools that use machine learning differ from traditional tools such as the FICO score. We then provide a step-wise description of how one might design and implement a

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[45]   *See* Marcus Tewksbury, *The 2013 Big Data Planning Guide for Marketers*, EXPERIAN   MARKETING   SERVICES   (2013), http://www.experian.com/assets/marketing-services/white-papers/big-data-planning-guide-for-marketers.pdf [https://perma.cc/FY9T-G28A].   Experian collects offline data for individual consumers that is linked to "match keys" like a consumer's address, credit card number, phone number, and also collects online and mobile data that is linked to match keys such as device ID, IP address, geolocation, a consumer's Twitter "handle," time stamp, and other identifiers.

[46]   Ann Carrns, *New Credit Score Systems Could Open Lending to More Consumers*,   N.Y.   TIMES   (Oct.   9,   2015) http://www.nytimes.com/2015/10/10/your-money/new-credit-score-systems-could-open-lending-to-more-consumers.html?_r=0   [https://perma.cc/JDW9-M7DD].

[47]   Robinson + Yu refer to such information as "mainstream alternative data," and suggest that by including factors such as payment histories into consumer credit scoring, models may be able to more effectively account for "thin-file" or "no-file" consumers who lack the traditional indicators of credit-worthiness, but who otherwise may be capable of taking on credit obligations. *See* Robinson + Yu, *supra* note 11, at 23.

[48]   *See id.* at 15.

machine-learning credit-scoring tool, drawing upon the real-world example of a new big-data credit-scoring company, ZestFinance. Finally, we describe the types of problems that may occur when machine learning is used to make credit decisions, examining how such big-data tools may be non-transparent and inaccurate, may perpetuate and deepen existing forms of discrimination, and may be used to unfairly target vulnerable consumers.

A. Introduction to basic terminology and concepts

In recent years, terms like "machine learning" and "algorithmic decision-making" have become staples in the popular discourse on big data. But these terms may remain opaque and mysterious to laypeople and lawyers alike. This section attempts to demystify some of these technical terms and concepts.

We begin with the most basic building block of our discussion: the algorithm. An algorithm can be described as "any well-defined computational procedure that takes some value, or set of values, as input and produces some value, or set of values, as an output. An algorithm is thus a sequence of computational steps that transforms the input into the output."[49] In lay terms, algorithms are simply mathematical formulae or models. Algorithms may range in their complexity from those used to solve very simple, well-defined problems to those used to solve complicated, ill-defined problems. Here, we describe well-defined problems as structured problems, and ill-defined problems as unstructured problems. Structured problems generally have only a single, certain answer for a set of input values.[50] For example, the arithmetic mean is an algorithm that takes a series of values as its inputs and produces the average of these values as its output.[51] Calculating the circumference of a circle based on the circle's radius is another example of a structured problem. Structured problems lack inherent randomness and uncertainty; as a consequence, the algorithms used to solve for structured problems generally remain fixed and do not change in response to different input variables.

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[49] *See* THOMAS H. CORMEN, CHARLES E. LEISERSEN, RONALD L. RIVEST, & CLIFFORD STEIN, INTRODUCTION TO ALGORITHMS 1 (3d ed. 2009) (emphasis omitted).

[50] An illustrative example is the conversion of inches to feet. By definition, 1 inch is equivalent to 0.0254 meters. In this case, 0.0254 meters is the only right answer to the "problem" of converting 1 inch to its equivalent in meters.

[51] *See* *Arithmetic Mean Definition*, INVESTOPEDIA, http://www.investopedia.com/terms/a/arithmeticmean.asp [https://perma.cc/T9GN-GH6D].

Algorithms can also be used to solve highly complex, unstructured problems where there is uncertainty in the underlying process as well as in the input data. Put simply, an unstructured problem can have multiple "correct" answers, although some of these correct answers may be better than others. In such cases, the formula (or formulae) used to arrive at a solution or output is often not static and can change depending on the input data.[52] Suresh Venkatasubramanian helpfully uses the analogy of a recipe to describe the types of algorithms used to solve unstructured problems.[53] For most dishes, like unstructured problems, there may not be a single, correct outcome and much depends upon the ingredients (or data) available to the cook.[54] There is, for example, no single, universal set of steps to prepare a ratatouille; optimal cooking times, ratios, seasonings, and preparatory steps may change depending on whether one uses eggplants or zucchini.

To offer another example from the commercial context, imagine that a retailer wishes to design a model that will segment customers into different groups and predict which sub-set of customers will respond favorably to targeted advertising. This customer segmentation challenge is an unstructured problem where there is likely no single "correct" formula for arriving at the desired end. The perceived relationships between customer characteristics and the customers' predicted responses to targeted ads might change when new data is added into the mix. Much like our hypothetical ratatouille chef, the data scientist who is tasked with designing a model to solve the customer segmentation problem might discover that there are many different ways to identify the subset of customers she seeks. The underlying algorithm or algorithms that make up the retailer's model are unlikely to remain static and can be expected to change in response to new input data.

The term "machine learning," which scholars suggest is related to, but different from, "data mining,"[55] describes "a set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to

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[52] There may also be inherent randomness or noise in the system being studied. A straightforward application of a mathematical formula would ignore the inherent noise in the system. *See* HAROLD J. KUSHNER & G. GEORGE YIN, STOCHASTIC APPROXIMATION ALGORITHMS AND APPLICATIONS 2 (1997).

[53] Suresh Venkatasubramanian, *When an Algorithm Isn't*, MEDIUM (Oct. 1, 2015), https://medium.com/@geomblog/when-an-algorithm-isn-t-2b9fe01b9bb5#.61b0z07a0 [https://perma.cc/U7SY-CK7Z].

[54] *Id.*

[55] *See* Toon Calders & Bart Custers, *What is Data Mining and How Does it Work?*, *in* DISCRIMINATION AND PRIVACY IN THE INFORMATION SOCIETY 29 (Bart Custers, et al. eds. 2012).

perform other kinds of decision making under uncertainty."[56] Once the process of machine learning is complete, the data scientist uses the patterns and insights detected in the data to design a final model (or set of models) that can predict a desired outcome. Returning to Venkatasubramanian's recipe analogy, imagine that we wish to make a certain known dish (the output), but we do not have a list of all of the ingredients (the inputs), or any information regarding the proper ratios for each ingredient. One method to arrive at the final recipe would be to assemble the whole universe of potential ingredients in our kitchen and prepare random combinations of these ingredients, discarding those ingredients that do not fit, and adding and adjusting new ingredients that improve the final result. If we continue with this process of trial and error, we may eventually stumble upon a final recipe that yields a palatable result.[57] The recipe analogy, although not perfect, offers a rough idea of how iterative machine learning works in practice. While this approach would be pretty inefficient in a kitchen, contemporary advances in computing power have made it possible for certain machine-learning tools to complete thousands and perhaps millions of iterations in a relatively short period of time.[58]

Machine learning comes in two flavors – "supervised" machine learning, and "unsupervised" machine learning. In the case of supervised machine learning, the data scientist has a known or desired output or "target variable," and wishes to discover the relationships between that target variable and various other data points that she may have at her disposal in order to predict when or why that output will occur. By allowing the data scientist to understand the relationship between the target variable and the various relevant input values, supervised machine learning can allow the data scientist to "predict the future value of a target variable as a function of [input values]."[59] Returning to our customer

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[56] Kevin P. Murphy, MACHINE LEARNING: A PROBABILISTIC PERSPECTIVE (2012).

[57] *See* Venkatasubramanian, *supra* at note 53.

[58] *See, e.g.*, Brad Brown, Michael Chui & James Manyika, *Are You Ready for the Era of 'Big Data'?*, MCKINSEY QUARTERLY (Oct. 2011), http://www.t-systems.com/solutions/download-mckinsey-quarterly-/1148544_1/blobBinary/Study-McKinsey-Big-data.pdf [https://perma.cc/B83D-RCUK]; Randal E. Bryant et al., *Big-Data Computing: Creating Revolutionary Breakthroughs in Commerce, Science, and Society* (Dec. 22, 2008), http://cra.org/ccc/wp-content/uploads/sites/2/2015/05/Big_Data.pdf [https://perma.cc/6979-N46J]; Robert L. Mitchell, *8 Big Trends in Big Data Analytics*, COMPUTERWORLD (Oct. 23, 2014), http://www.computerworld.com/article/2690856/big-data/8-big-trends-in-big-data-analytics.html [https://perma.cc/PUA6-NBVV].

[59] COMMITTEE ON THE ANALYSIS OF MASSIVE DATA, ET AL., FRONTIERS IN MASSIVE DATA ANALYSIS 101 (2013), http://www.nap.edu/read/18374/chapter/9#101

segmentation example, a retailer might possess customer records that indicate whether certain customers have responded favorably to targeted advertising on past occasions. But the retailer may have no idea why certain customers responded as they did or what advertising techniques were effective. Depending on the body of data points available, the retailer can use a machine-learning process to understand the factors that are correlated to the retailer's target variable – customer responsiveness to targeted advertising – and this in turn will assist the retailer in developing a more effective advertising strategy.

In the case of unsupervised machine learning, the data scientist may not have anything specific that she wishes to predict or determine, meaning that the process is not focused on understanding a known target variable. Unsupervised learning can, however, illuminate relationships between data points that may be useful in the future.[60] Through unsupervised learning, the data scientist can "understand how the data were generated, the relationships between variables, and any special structure that may exist in the data."[61]

With these basic terms and concepts in mind, we next describe how big data and algorithmic decision making are changing the credit-scoring and lending industries.

B. How traditional credit-modeling tools compare to alternative, "big-data" tools

Estimating an individual's creditworthiness is an unstructured problem. There exists no single rule to predict a borrower's likelihood of repayment. Historically, credit-scoring companies like The Fair Isaac Corporation (FICO) have used relatively simple algorithmic solutions that integrate a limited number of categories of data.[62] The basic FICO score, for instance, considers an individual's payment history, outstanding debt, length of credit history, pursuit of new credit, and debt-to-credit ratio in determining a credit score.[63] The model assigns a numeric value for each of these five variables,[64] and then applies a pre-determined weight (in percentage

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[https://perma.cc/Z49D-7FBE]. As used in this paper, the term "target variable" refers to an example of the desired output.

[60] For a more complete explanation of unsupervised learning techniques and applications, see Toon Calders & Bart Custers, supra note 55, at 27-42.

[61] COMMITTEE ON THE ANALYSIS OF MASSIVE DATA, ET AL., supra note 59.

[62] See Rob Berger, A Rare Glimpse Inside the FICO Credit Score Formula, DOUGHROLLER (Apr. 30, 2012), http://www.doughroller.net/credit/a-rare-glimpse-inside-the-fico-credit-score-formula [https://perma.cc/8VD7-6JSX].

[63] Id.

[64] Id.

terms) to each of these input values and averages them to arrive at a final credit score.[65]

While the FICO model may be simple to apply and relatively easy for a loan applicant to understand, this simplicity may also lead to credit decisions that are under-inclusive and that disadvantage borrowers who have not had prior access to the credit system.[66] An individual's relative ability to repay a loan may depend on myriad factors, and a more nuanced model that integrates a wider variety of data points could, at least arguably, solve the under-inclusivity problem. Until very recently, lenders and underwriters faced technological constraints that limited their ability to collect, store, and analyze data about prospective applicants.[67] Increasingly, however, credit scorers are able to take advantage of a wide variety of non-traditional data, including information collected from social media, consumers' retail spending histories, and other data points obtained from public platforms or procured from data brokers.[68] In order to effectively analyze this wealth of data on consumers' online and offline activity, the alternative credit-scoring industry is turning to more complicated algorithms and modeling techniques.[69] In an ideal world, the more sophisticated the algorithms used and the more data involved, the more predictive and accurate a credit-scoring model should be. As we explore in greater detail below, however, big-data tools also pose significant risks to transparency, accuracy, and fairness.

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[65] *Id.*

[66] *See supra* note 20.

[67] *See* Eva Wolkowitz & Sarah Parker, *Big Data, Big Potential: Harnessing Data Technology for the Underserved Market*, CENTER FOR FINANCIAL SERVICES INNOVATION 4 (2015), http://www.morganstanley.com/sustainableinvesting/pdf/Big_Data_Big_Poten tial.pdf [https://perma.cc/CC72-X7RE] ("Consumer finance applications of Big Data have existed ever since credit bureaus first gathered tradeline information to assign consumer repayment risk[,] and insurance companies utilized applicant histories and demographics to set premiums[.] . . . The earliest uses of large data sets to inform financial product offerings did not differ greatly, in theory or aim, from how Big Data usage is conceived today. Rather, its use was limited by rudimentary computing power and the hurdles of gathering and normalizing data from incompatible or non-digitized sources, both of which made the process relatively inefficient.")

[68] *See id.* at 14, 23; *see also, e.g.*, Bill Hardekopf, *Your Social Media Posts May Soon Affect Your Credit Score*, FORBES (Oct. 23, 2015), http://www.forbes.com/sites/moneybuilder/2015/10/23/your-social-media-posts-may-soon-affect-your-credit-score-2/#28ba380a3207 [https://perma.cc/86XS-7F7A].

[69] Robinson & Yu, *supra* note 11, at 2.

One of the most prominent players in the alternative credit-scoring and underwriting industry is ZestFinance.[70] Founded in 2009, ZestFinance offers big-data credit-scoring tools to providers of payday loans (short-term, high-interest loans), while also offering such loans through its affiliate, ZestCash.[71] To date, the company has underwritten "more than 100,000 loans" and is authorized to lend to consumers in several states across the United States.[72] ZestFinance touts an "all data is credit data" approach[73] that combines conventional credit information with thousands of data points collected from consumers' offline and online activities. The company's system of proprietary algorithms analyzes several thousand data points per individual in order to arrive at a final score.[74] While ZestFinance has not disclosed detailed information regarding either its data sources or the algorithms it uses, a patent application[75] and marketing materials provide a window onto ZestFinance's scoring system.

Consumers would likely be surprised at the types of information ZestFinance uses to predict creditworthiness. Although ZestFinance does rely upon some traditional credit data, other data points may appear to have little connection to creditworthiness. For example, the ZestFinance model takes into consideration how quickly a loan applicant scrolls through an online terms-and-conditions disclosure, which – according to the company's founder – could indicate how responsible the individual is.[76] Evidence that a person is willing to give up

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[70] *See* Steve Lohr, *Big Data Underwriting for Payday Loans*, N.Y. TIMES (Jan. 19, 2015), http://bits.blogs.nytimes.com/2015/01/19/big-data-underwriting-for-payday-loans/?_r=0 [https://perma.cc/YE7F-NS6E].

[71] *See* ZESTCASH, https://www.zestcash.com [https://perma.cc/VW2Q-ZLKG]. ZestFinance insists that it does not engage in payday lending, however as the *New York Times* points out, the products offered through ZestCash feature extremely high rates of interest, and ZestCash may deduct sums from borrowers' accounts on paydays. ZeshCash is no longer in operations as of June 24, 2016. *See* Ann Carrns, *Don't Call them Payday Loans, but Watch the Fees*, N.Y. TIMES (Feb. 15, 2012), http://bucks.blogs.nytimes.com/2012/02/15/dont-call-them-payday-loans-but-watch-the-fees [https://perma.cc/L2PF-JKU2].

[72] Lohr, *supra* note 70, N.Y. TIMES (Jan. 19, 2015).

[73] *See supra* note 9.

[74] Michael Carney, *Flush with $20M from Peter Thiel, ZestFinance is Measuring Credit Risk Through Non-traditional Big Data*, PANDO (July 31, 2013), http://pando.com/2013/07/31/flush-with-20m-from-peter-thiel-zestfinance-is-measuring-credit-risk-through-non-traditional-big-data [https://perma.cc/PZ5R-WPJG].

[75] U.S. Patent App. No. 14/276,632 (filed May 13, 2014), http://www.google.com/patents/US20150019405 [https://perma.cc/3CM2-RK2Z].

[76] Quentin Hardy, *Big Data for the Poor*, N.Y. TIMES (July 5, 2012), http://bits.blogs.nytimes.com/2012/07/05/big-data-for-the-poor [https://perma.cc/88NM-KZPW].

social-media connections might likewise signal a high-risk borrower.[77] ZestFinance also considers spending habits in the context of a borrower's geographic location. For instance, "paying half of one's income [on rent] in an expensive city like San Francisco might be a sign of conventional spending, while paying the same amount in cheaper Fresno could indicate profligacy."[78]

ZestFinance is only one example of an alternative credit-scoring company that claims to predict credit risk on the basis of non-traditional data. The methods and practices of the alternative credit-scoring industry as a whole remain opaque and poorly understood. According to Upturn's David Robinson and Harlan Yu, "[t]hese companies come and go quickly, making it difficult to construct a complete snapshot of the market."[79] In a recent study of alternative credit-scoring models, Upturn identified a number of "fringe" data scoring products available from both established and startup credit-scoring companies (*see* Table 1).[80]

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[77] *Id.*
[78] *Id.*
[79] Robinson + Yu, *supra* note 11, at 14.
[80] Adapted from Robinson + Yu, *supra* note 11, at 13-15.

Tbl. 1. Examples credit scorers using non-traditional data

Company & Product	Example Data Inputs
LexisNexis – RiskView	Residential stability, asset ownership, life-stage analysis, property deeds and mortgages, tax records, criminal history, employment and address history, liens and judgments, ID verification, and professional licensure.
FICO – Expansion Score	Purchase payment plans, checking accounts, property data, public records, demand deposit account records, cell and landline utility bill information, bankruptcy, liens, judgments, membership club records, debit data, and property asset information.
Experian – Income Insight	Rental payment data, public record data.
Equifax – Decision 360	Telco utility payments, verified employment, modeled income, verified income, spending capacity, property/asset information, scheduled monthly payments, current debt payments, debt-to-income ratio, bankruptcy scores.
TransUnion – CreditVision	Address history, balances on trade lines, credit limit, amounts past due, actual payment amount.
ZestFinance	Major bureau credit reports and thousands of other variables" including financial information, technology usage, and how quickly a user scrolls through terms of service.
LendUp	Major bureau credit reports, social network data, how quickly a user scrolls through its site.
Kreditech (Not available in U.S.)	Location data (e.g., GPS), social graphing (likes, friends, locations, posts), behavioral analytics (movement and duration on a webpage), e-commerce shopping behavior, device data (apps installed, operating systems).
Earnest	Current job, salary, education history, balances in savings or retirement accounts, online profile data (e.g., LinkedIn), and credit card information.
Demyst Data	Credit scores, occupation verification, fraud checks, employment stability, work history, and online social footprint.

What little information is available about these alternative credit-assessment tools is already provoking alarm among regulators and consumer-advocacy groups.[81] There is concern that these tools are non-transparent and rely on inaccurate data collected from numerous sources, making it difficult for consumers to verify or challenge unfair decisions. As already noted above, inaccuracies in raw credit-reporting

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[81] *See, e.g.*, Pam Dixon & Robert Gellman, *The Scoring of America: How Secret Consumer Scores Threaten Your Privacy and Your Future*, WORLD PRIVACY FORUM (Apr. 2, 2014), http://www.worldprivacyforum.org/wp-content/uploads/2014/04/WPF_Scoring_of_America_April2014_fs.pdf [https://perma.cc/FY3V-TSGU]; Robinson + Yu, *supra* note 11; YU ET AL., *supra* note 10, at 27.

data have posed frequent problems for traditional credit-scoring and assessment tools.[82]

These tools may also perpetuate and, indeed, intensify, existing bias by scoring consumers on the basis of their religious, community, and familial associations, as well as on the basis of sensitive features such as race or gender. The social-media company Facebook recently filed a patent application pertaining to a method for "[a]uthorization and [a]uthentication [b]ased on an [i]ndividual's [s]ocial [n]etwork."[83] The patent application indicates that one of the method's preferred embodiments could be used for credit scoring.[84] The patent application explains that: "[w]hen an individual applies for a loan, the lender [could] examine[] the credit ratings of members of the individual's social network who are connected to the individual. . . If the average credit rating of these members is at least a minimum credit score, the lender [could] continue[] to process the loan application. Otherwise, the loan application [would be] rejected."[85] Although it is unclear whether Facebook's credit-scoring tool is operational, critics have already suggested that the tool could lead to new forms of digital redlining.[86]

There is also no certainty that all the alternative credit-assessment tools on the market are truly designed to predict creditworthiness; instead, some may be designed to identify and target vulnerable individuals with high-cost loan products. Although there is no concrete evidence showing that alternative scorers are currently using machine learning to identify such borrowers, major data brokers, some of whom are also engaged in credit reporting, have been criticized for selling so-called "sucker lists" that identify individuals who are "old, in financial distress, or otherwise vulnerable to certain types of marketing pitches."[87] In one high-profile example, the FTC sought a consent decree against Equifax for selling lists of potentially vulnerable consumers to companies that market fraudulent products.[88] A 2013 Senate Commerce Committee

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[82] *See, e.g.*, Brief for Center for Dig. Democracy as Amicus Curiae Supporting Respondents, *Spokeo, Inc. v. Robins*, 135 S.Ct. 1892, No. 13-1339, 2015 WL 5302538, at *12-13; *see also supra* note 16.

[83] U.S. Patent No. 9,100,400 (filed Aug. 2, 2012).

[84] *Id.*, Col. 2, ls. 9-16.

[85] *Id.*, Col. 2, ls. 10-16.

[86] Robinson Meyer, *Could a Bank Deny Your Loan Based on Your Facebook Friends?*, The Atlantic (Sept. 25, 2015), http://www.theatlantic.com/technology/archive/2015/09/facebooks-new-patent-and-digital-redlining/407287 [https://perma.cc/73Y5-YY48].

[87] Julia Angwin, Dragnet Nation: A Quest for Privacy, Security, and Freedom in a World of Relentless Surveillance (2014).

[88] *Equifax Information Services, LLC*, Complaint No. 102-3252, Fed. Trade Comm'n   (2012),

report also described some of these lists, which, with titles such as "Hard Times," "Burdened by Debt," "Retiring on Empty," and "X-tra Needy," appear deliberately calibrated to single out consumers who are most susceptible to unfavorable financial products like payday loans.[89] As one report suggests, if "secretive, data-driven scoring" can be used to identify vulnerable consumers, this could "trigger a flood of payday loan ads" targeted to these individuals.[90]

To better understand how these risks may arise, it is useful to first understand how an alternative credit scorer might use machine-learning techniques and thousands of data points to model and predict creditworthiness.

C. Using machine learning to build a big-data credit-scoring model – how it works and potential problems

How would a data scientist go about solving the unstructured problem of measuring creditworthiness using thousands of available data points and supervised machine-learning tools? There is no single methodology to design a big-data credit-scoring tool, and every scorer's data-driven recipe is likely to differ. To the extent generalization is possible, this part describes the three major steps that a credit scorer might follow to design its scoring tool, namely: i) defining the problem to be solved (the scorer's definition of creditworthiness) and specifying a target variable representing the outcome the scorer wishes to predict; ii) gathering data and transforming it into useable form; and, iii) developing and refining the model through exposure to training data and through feature selection. These three steps generally reflect the process that ZestFinance outlines in its patent application for its alternative credit-scoring tool. A schematic of ZestFinance's model and scoring system is provided in *Figure 1*, below.

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https://www.ftc.gov/sites/default/files/documents/cases/2012/10/121010equifax cmpt.pdf [https://perma.cc/ZCP5-VRSC].

[89] STAFF OF CHAIRMAN ROCKEFELLER, S. COMM. ON COMMERCE, SCI. & TRANSP., 113TH CONG., A REVIEW OF THE DATA BROKER INDUSTRY 24 (Comm. Print 2013) http://www.commerce.senate.gov/public/_cache/files/bd5dad8b-a9e8-4fe9-a2a7-b17f4798ee5a/D5E458CDB663175E9D73231DF42EC040.12.18.13-senate-commerce-committee-report-on-data-broker-industry.pdf [https://perma.cc/2RNT-LZ4V].

[90] Jeff Chester & Edmund Mierzwinski, *Big Data Means Big Opportunities and Big Challenges: Promoting Financial Inclusion and Consumer Protection in the "Big Data" Financial Era*, U.S. PIRG EDUC. FUND & CTR. FOR DIG. DEMOCRACY 13 (2014), https://www.democraticmedia.org/sites/default/files/field/public-files/2015/uspirgefandcddbigdatareportmar14_1.3web.pdf [https://perma.cc/V9TC-WKJJ].

Fig. 1: ZestFinance's modeling & scoring process[91]
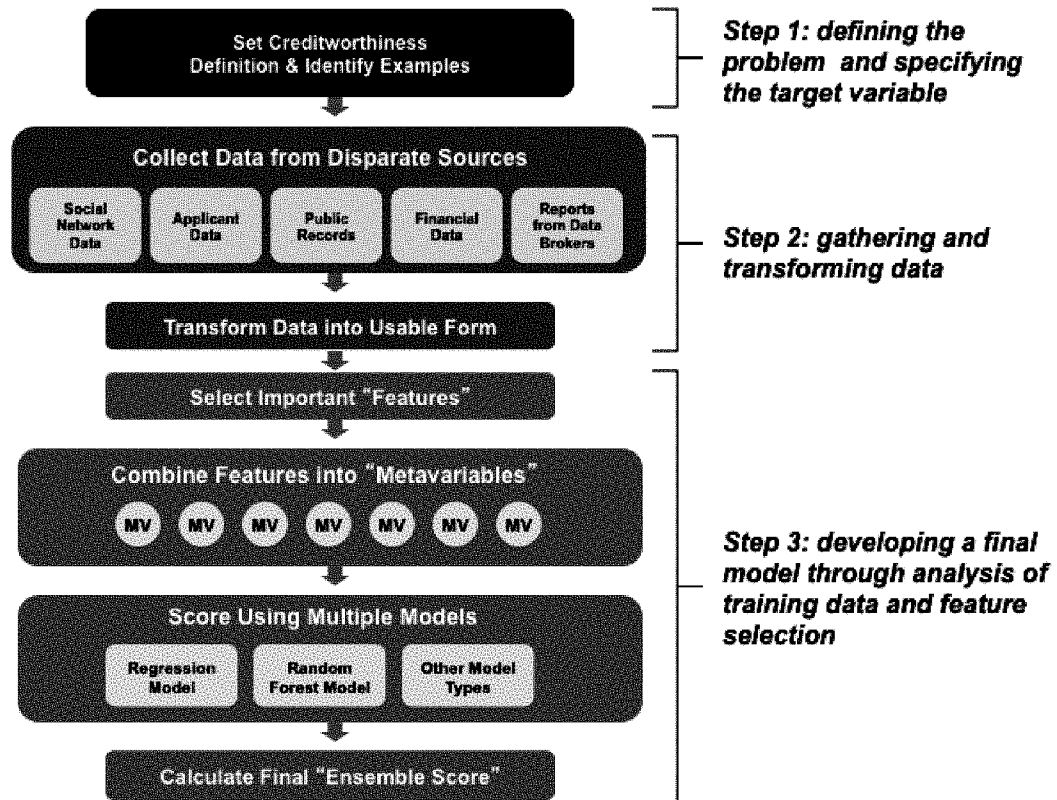
It is important to note that the supervised machine-learning process we describe in this part is highly simplified. In practice, the process of arriving at a model for a complex, unstructured problem such as predicting creditworthiness is likely to be iterative. For example, the scorer may constantly update it stock of data or integrate new types of data, which could ultimately lead to changes in the structure of the model, the model's most significant features, or the weights assigned to these features. This part offers a simplified snapshot of some of the key steps in this ordinarily iterative process.

i) Step 1: defining the problem and specifying the target variable

Before using supervised machine-learning techniques to solve a problem or make predictions, the data scientist must first define the problem and determine precisely what she

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[91] Adapted from U.S. Patent App. No. 14/276,632, *supra* note 75.

wishes to predict.[92] This step may seem obvious, but in the case of an unstructured problem like predicting creditworthiness, where there is no single correct answer, articulating a proper and quantifiable definition is critical. To explain, we return to our example of the retailer who wishes to segment customers into different groups and predict which sub-set of customers are most likely to respond favorably to targeted advertising. There is no predefined formula or rule to tell us why certain customers respond to targeted ads, when others do not. The data scientist must "translate some amorphous problem into a question that can be expressed in more formal terms that computers can parse."[93]

One way to achieve this is to select a "state or outcome of interest" commonly referred to as a "target variable."[94] A target variable can be defined by reference to examples of past outcomes or varying characteristics.[95] These differing outcomes or characteristics are often described as "class attributes."[96] For example, suppose our retailer previously circulated a promotional email to a list of known customers, and the email contained an offer for a product at a reduced price. Suppose further that, in order to obtain the discounted product, customers had to purchase the product at the retailer's online shop using a discount code supplied in the email. At the end of the promotion period, the retailer would have a list of customers that responded, as well as a list of customers that did not respond. These two lists would correspond to two classes representing responsiveness to targeted advertising, which is the target variable of interest. The class attribute for this first group could be encoded as "responsive to targeted advertising." The class attribute for the second group could be encoded as "non-responsive to targeted advertising." The classes of customers on both the responsive list and the non-responsive list could then be used to make predictions about future customer behavior.

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92 *See* Dean Abbot, *Why Defining the Target Variable in Predictive Analytics is Critical*, DATA MINING AND PREDICTIVE ANALYTICS (Apr. 5, 2012), http://abbottanalytics.blogspot.com/2012/04/why-defining-target-variable-in.html [https://perma.cc/FHM2-49F2].

93 Solon Barocas & Andrew D. Selbst, *Big Data's Disparate Impact*, 104 CALIF. L. REV. (forthcoming 2016) (manuscript at *8).

94 *Id.* at *7-8; *see also* COMMITTEE ON THE ANALYSIS OF MASSIVE DATA, ET AL, *supra* note 59, at 101 (describing how machine learning models allow for the "predict[ion of] the future value of a target variable as a function of the other variables at one's disposal, and/or at a future time").

95 *See* Abbot, *supra* note 92.

96 Toon Calders & Indrė Žliobaitė, *Why Unbiased Computational Processes Can Lead to Discriminative Decision Procedures*, *in* DISCRIMINATION AND PRIVACY IN THE INFORMATION SOCIETY 44 (Bart Custers, et al. eds. 2012).

While the retailer's approach to defining a target variable and establishing class attributes in this example might seem logical, it could also result in flawed predictions because the class groupings are broad. The class represented by the non-responsive group is the most troublesome because the retailer only knows that non-responsive customers did not purchase the product online, but cannot say why. Some non-responsive customers may truly have been uninfluenced or even negatively influenced by the ad. Others may have failed to respond for a variety of different reasons. For example, certain non-responsive customers might use automatic spam filters on their email inboxes that prevented those customers from receiving an ad that they would otherwise have found useful. Other non-responsive customers might not have actually seen the email until after the promotional period lapsed, and thus could not use the code even if they had wanted to do so. Some non-responsive customers may actually have been influenced by the email, but they may have purchased the product at brick-and-mortar stores, rather than online.[97] Finally, recall that the retailer based its target variable on a sample population of customers whose email addresses were previously known to the retailer. If this sample population is not representative of the general population of all potential customers, the retailer's target variable and class groups are likely to be under-inclusive and only of partial predictive value.[98]

While a careful data scientist would likely anticipate these types of problems, the retailer example illustrates the challenges that a data scientist may face when attempting to reduce a complex problem into a quantifiable target variable and set of class attributes. Depending on the information available to the data scientist, there may not be a cost-effective way to increase the granularity of the class attributes, ultimately reducing the accuracy of the final model. It may also prove expensive and burdensome for the data scientist to ensure that the individuals in the initial data set reflect the same distribution of characteristics in the broader population that the data scientist wishes to study.[99]

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[97] Dean Abbot offers a similarly illustrative example of flawed target variable definition involving cases of fraud. *See* Dean Abbot, *supra* at note 92.

[98] As Kate Crawford points out, when target variables are under-inclusive due to gaps in the data set, there may be "signal problems" where "some citizens and communities are overlooked or underrepresented." Kate Crawford, *Think Again: Big Data*, FOREIGN POLICY (May 9, 2013), http://foreignpolicy.com/2013/05/10/think-again-big-data [https://perma.cc/EF5B-XK8E].

[99] *See* Toon Calders and Indrė Žliobaitė, *supra* at note 96, 46-47 ("Computational models typically [assume] . . . that (1) the characteristics of

Credit scoring, while more complex than our targeted-advertising example, arguably poses many of the same challenges. There is no inherent definition of "creditworthiness." Instead, as Barocas and Selbst note:

> [T]he very notion of creditworthiness is a function of the particular way the credit industry has constructed the credit issuing and repayment system—one in which an individual's capacity to repay some minimum amount of an outstanding debt on a monthly basis is taken to be a non-arbitrary standard by which to determine in advance and all-at-once whether he is worthy of credit.[100]

There are multiple possible options for the data scientist who wishes to define creditworthiness and establish a target variable that can be used for future predictions. One option might be to simply segment potential borrowers into classes (e.g., "very creditworthy," "creditworthy," "less creditworthy," and "not creditworthy") based on their FICO scores. Another option might be to segment borrowers based upon their income levels and credit card repayment histories. Individuals with low incomes, or those that did not regularly pay down credit card balances, might be deemed less creditworthy, whereas those with higher incomes and strong track records of repayment might be deemed more creditworthy. Either option is likely to have its shortcomings. For example, basing class groups on borrowers' existing FICO scores could systematically exclude some populations that have been historically unrepresented in the credit market, potentially for reasons that have little to do with these groups' capacity to be responsible borrowers.[101] An approach that classifies borrowers based on their relative income levels or past repayment histories may be overly simplistic and may fail to account for other factors that bear on a particular borrower's ability to repay a loan.

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the population will state the same in the future when the model is applied and (2) the training data represents the population well. These assumptions are known as the *i.i.d.* setting, which stands for *independently identically distributed* random variables").

[100] Barocas and Selbst, *supra* at note 93, at 9 (citing David J. Hand, *Classifier Technology and the Illusion of Progress*, 21 STATISTICAL SCI. 1 (2006)).

[101] *See, e.g.*, Blake Ellis, *Millions Without Credit Scores not so Risky After All*, CNN MONEY (Aug. 14, 2013), http://money.cnn.com/2013/08/14/pf/credit-scores [https://perma.cc/4GD4-PPN5].

A poorly-crafted definition could also lead to inadvertent discrimination, where "data miners [] unintentionally parse the problem and define target variables in such a way that protected classes happen to be subject to systematically less favorable determinations."[102] As Calders and Žliobaitė point out, the process of assigning labels to class attributes may be either objective or subjective.[103] Subjective labeling involves some human interpretation, whereas objective labeling does not.[104] The class attributes in our retail example are objective: customers fall within binary categories based on their responses to the targeted advertisement. Subjective class labels, by contrast, are generally non-binary, for example "the assessment of a human resource manager [regarding whether] a job candidate is suitable for a particular job."[105] Where class attributes are defined subjectively, "there is a gray area in which human judgment may have influenced the labeling resulting in bias."[106] As we note in further detail below, the class attributes that the data scientist initially selects may be adjusted and perhaps even supplanted as the machine-learning process advances. However, there is no guarantee that the machine-learning process will necessarily correct for implicit bias that is initially introduced through poorly-defined target variables or class attributes.

Alternative credit scorers promise that they can avoid problems of under-inclusiveness posed by traditional scoring systems,[107] but so far, it remains unclear whether this truly is the case. Unfortunately, there is scarce information about how alternative credit-scoring companies like ZestFinance define "creditworthiness," or how they set target variables and label classes of borrowers to serve as examples for their machine-learning processes.[108] ZestFinance's patent application does not supply its definition of creditworthiness, or describe the target variable it uses.

Although there is no clear-cut evidence that alternative credit-scoring companies are using machine-learning tools to maximize lender profitability at the expense of consumers,

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[102] Barocas and Selbst, *supra* at note 93, at 8.
[103] Toon Calders and Indrė Žliobaitė, *supra* at note 55, at 48.
[104] *Id.*
[105] *Id.*
[106] *Id.*
[107] ZestFinance claims that its machine-learning system "allows a lender to utilize new sources of information to compile risk profiles in ways traditional models could not accomplish, and in turn serve a completely new market," thereby increasing credit access to the historically "underbanked." U.S. Patent App. No. 14/276,632, *supra* note 75, at ¶ 0011.
[108] ZestFinance's patent application makes frequent reference to the term "creditworthiness" without any indication of a definition or paradigm target variable. *See, e.g., id.* at ¶ 0003.

rather than scoring for "creditworthiness" as the layperson might understand it, there is also no reason to assume that these companies have the borrowers' interests at heart. A recent study of online payday lending notes that the "lenders [using] sophisticated technology and advanced algorithms to predict which applicants are most likely to repay loans . . . continue to charge interest rates usually in excess of 300 percent APR...."[109] Experts at Upturn have also recently detailed how online "lead generators" are using sophisticated algorithmic scoring techniques to zero in on consumers at moments when they are likely to be especially vulnerable to low-value, short-term credit products with usurious interest rates and highly unfavorable terms.[110] This raises the possibility that certain alternative credit scorers may not be truly interested in predicting consumer creditworthiness, but rather in finding vulnerable, high-value targets for unfavorable loans.[111] Payday borrowers also "disproportionately come from poor and minority communities."[112] Rather than expanding access to underserved groups, alternative credit scorers may be employing target variables that work to the further detriment of historically disadvantaged groups.

ii)   Step 2: gathering and transforming data

Once the data scientist has identified the target variable and established classes, she next gathers information associated with individuals for which the various outcomes are already known. This information will eventually constitute the "training data" that will be used throughout the machine-learning process to develop a final model. The prevailing view is that the larger the data set available for analysis, the more accurate and predictive the final model. In the era of "big data," alternative credit-scoring companies can take advantage of the booming trade in consumer information to obtain everything from an individual's online purchase history, criminal and arrest record, internet browsing history (collected

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[109] Nick Bourke et al., *Fraud and Abuse Online: Harmful Practices in Internet Payday Lending*, THE PEW CHARITABLE TRUSTS 4 (2014), http://www.pewtrusts.org/~/media/Assets/2014/10/Payday-Lending-Report/Fraud_and_Abuse_Online_Harmful_Practices_in_Internet_Payday_L ending.pdf [https://perma.cc/M8UD-9EM5].

[110] *See* Upturn, *Led Astray: Online Lead Generation and Payday Loans* (Oct. 2015), https://www.teamupturn.com/reports/2015/led-astray [https://perma.cc/42VF-VEW4].

[111] As already discussed above in Section III (B) *supra*, certain major credit-reporting agencies and data brokers have been subject to investigation and public criticism for selling "sucker lists" with information on financially-vulnerable consumers.

[112] *Id.*

through tracking mechanisms such as browser "cookies"), to an individual's "friend" groups on social-media platforms.[113]

ZestFinance's approach to gathering data is illustrative. ZestFinance claims to collect thousands of data points for each individual it analyzes. These data points fall into four broad categories, namely: 1) the borrower's data, 2) proprietary data, 3) public data, and 4) social network data.[114] The first category contains information provided directly by the applicant during the application process,[115] as well as other information such as web-browser activity, which might be gleaned from the applicant's device at the time she applies for a loan online.[116] For example, if a prospective customer applies online, ZestFinance may be able to measure how long the applicant spends reviewing the terms and conditions page to determine whether she read it carefully.[117] The second category, "proprietary data," refers to information obtained from "privately or governmentally owned data stores,"[118] and most likely includes material complied by major data brokers such as Acxiom.[119] This second category is perhaps the broadest, and may encompass everything from an individual's online and offline purchase history to health and medical data.[120] The third category, "public data," contains information that ZestFinance obtains from automated searches of the Internet and techniques such as web crawling and scraping.[121] Finally, the fourth category, "social network data," consists of social-media activity including information aggregated from the borrower's social media posts and "any social graph

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[113] A *New York Times* report concludes, "[I]t's as if the ore of our data-driven lives were being mined, refined and sold to the highest bidder, usually without our knowledge – by companies that most people rarely even know exist." *See* Singer, *supra* note 8.

[114] U.S. Patent App. No. 14/276,632, *supra* note 75, at ¶ 0038.

[115] *Id.* at ¶ 0028.

[116] *Id.*

[117] *Id.* at ¶ 0040.

[118] *Id.* at ¶ *0025.*

[119] *See* Singer, *supra* note 8. According to Singer, as of 2012, Acxiom's "servers process[ed] more than 50 trillion data 'transactions,'" and that the company's "database contains information about 500 million active consumers worldwide, with about 1,500 data points per person. That includes a majority of adults in the United States."

[120] According to Adam Tanner, data brokers may increasingly be able to gather information on individuals' prescription histories in a manner that sidesteps the protections of Federal privacy laws such as HIPAA. *See* Adam Tanner, *How Data Brokers Make Money Off Your Medical Records*, SCIENTIFIC AMERICAN (Feb. 1, 2016), http://www.scientificamerican.com/article/how-data-brokers-make-money-off-your-medical-records [https://perma.cc/WSJ2-GUX5].

[121] U.S. Patent App. No. 14/276,632, *supra* note 75, at ¶ 0026.

information for any or all members of the borrower's social network."[122]

Once the data scientist has collected the raw data points that will serve as training data, she must translate them into a usable form that can be processed by a computer. The ZestFinance patent provides some insights into how such a transformation process works.[123] For instance, an individual's raw salary might be translated into a percentile score that compares the individual's salary to the salaries of other people who are employed in the same industry and geographic region.[124] As another example, recall that ZestFinance collects information about the amount of time that an applicant spends reviewing a terms-and-conditions disclosure, which ZestFinance sees as an indicator of an applicant's level of responsibility. However, this raw time measurement is not immediately useable, and ZestFinance transforms the measurement into "an ordinal variable on a 0-2 scale, where 0 indicates little or no care during the application process and 2 indicates meticulous attention to detail during the application process."[125]

ZestFinance's data-transformation process does not end here, however. After converting the raw data points into useable form, ZestFinance further processes the resulting variables "using one or more algorithms (statistical, financial, machine learning, etc.) to generate a plurality of independent decision sets describing specific aspects of a borrower," which the patent refers to as "metavariables."[126] ZestFinance's metavariables appear to place applicants into categories by drawing inferences from one or more pieces of transformed data. For example, a metavariable might compare an applicant's reported income to the average income of individuals with similar professions living in the applicant's city, and then generate a "veracity check" that represents the likelihood that the applicant is misrepresenting her salary.[127] As another example, ZestFinance might score the applicant on a "personal stability" scale, based upon the amount of time she has "been consistently reachable at a small number of addresses or phone numbers."[128] The patent explains that ZestFinance's metavariables are "very useful at the

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[122] *Id.* at ¶ 0027.
[123] *Id.* at ¶¶ 0040-42.
[124] *Id.* at ¶ 0042.
[125] *Id.*
[126] *Id.* at ¶ 0041.
[127] *Id.* at ¶ 0044.
[128] *Id.*

intermediate stage of constructing a credit scoring function,"[129] and may be used to determine "which 'signals' are to be measured [in the final scoring process], and what weight is to be assigned to each ['signal']."[130]

The process of data collection and transformation poses a number of risks that, if left unaddressed, may lead to unfair denials of credit or extension of credit under unfavorable terms. One such risk may occur when the credit scorer has an overabundance of data points at its disposal. While the integration of more training data into a machine learning process may lead to increased accuracy in the modeling,[131] it can also increase the incidence of spurious correlations.[132] As data scientist James Kobielus notes, "[o]ne of the bedrock truths of statistics is that, given enough trials, almost any possible occurrence can happen . . . . The more possible events that might take place, the more potential, albeit unlikely, 'fluke' events there are."[133] As credit-scoring algorithms integrate more inputs, it becomes more likely that an algorithm might draw a spurious correlation between a particular attribute and creditworthiness. As Kobielus further explains:

> Some extreme correlations may jump right out at us and scream "Significant!" only to fade upon repeated observations. Though they may not be statistical flukes, such correlations may vanish under the influence of the statistical rule known as "regression toward the mean." These are non-robust correlations of the sort that may be borne out by historical data sets but, when encoded in predictive models, fail to be replicated in future observations.[134]

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[129] The Metavariables serve as the inputs to the final scoring model. *See id.* at ¶ 0043.

[130] *Id.* at ¶ 0045.

[131] *Cf.* Keith G. Calkins, *Applied Statistics Lesson 11: Power and Sample Size,* ANDREWS UNIVERSITY (July 28, 2005), http://www.andrews.edu/~calkins/math/edrm611/edrm11.htm [https://perma.cc/3R7E-398L] (explaining that a greater sample size leads to more power in a statistical test, which can be applied to the context of machine learning).

[132] David Bollier, *The Promise and Peril of Big Data,* ASPEN INSTITUTE, at 5, 14 (Jan. 1, 2010), https://www.aspeninstitute.org/publications/promise-peril-big-data [https://perma.cc/RB5Q-6TJ5].

[133] James Kobelius, *Big data's bogus correlations,* IBM BIG DATA & ANALYTICS HUB (May 22, 2014), http://www.ibmbigdatahub.com/blog/big-datas-bogus-correlations [https://perma.cc/386N-FLG8].

[134] *Id.*

The raw input data is also not necessarily objective; indeed, it is likely to reflect forms of preexisting bias and discrimination. As one expert has warned, "because not all data is created or even collected equally, there are 'signal problems' in big-data sets – dark zones or shadows where some citizens and communities are overlooked or underrepresented."[135] Such signal problems may arise where the mechanisms used to collect data favor particular groups to the exclusion of others. Kate Crawford points to the example of Boston's "Street Bump" app[136] to explain how the design of a data collection tool can lead to different outcomes for similarly-situated groups.[137] Street Bump uses the accelerometers in motorists' iPhones to crowd-source data on the location of potholes. As Crawford notes, "if cities begin to rely on data that only come from citizens with smartphones, it's a self-selecting sample – it will necessarily have less data from those neighborhoods with fewer smartphone owners, which typically include older and less affluent populations."[138] If credit scorers rely on non-neutral data collection tools that fail to capture a representative sample of all groups, some groups could ultimately be treated less favorably or ignored by the scorer's final model.

Another challenge posed by the use of extremely large data sets is the problem of accuracy, something that has long plagued traditional credit scorers who have historically relied on far fewer data points than those in the alternative scoring industry. As mentioned above, in a 2013 study, the FTC identified a high incidence of inaccuracies in traditional credit reports, leading to elevated rates of interest for certain borrowers.[139] A recent study by the National Consumer Law Center that examined the consumer information held by a number of major data brokers likewise concluded that the data sources used by alternative credit scorers were "riddled with inaccuracies," ranging from "the mundane" to the "seriously flawed."[140] According to the Electronic Privacy Information Center, because big-data credit scorers are principally "concerned with amassing a large quantity of information about an individual," the overall quality of that data is likely to suffer.[141]

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[135] Crawford, *supra* note 98.
[136] *See* Street Bump, http://www.streetbump.org [https://perma.cc/CXC2-75WZ].
[137] Crawford, *supra* note 98.
[138] *Id.*
[139] FED. TRADE COMM'N, *supra* note 14, at 63-64.
[140] *See* Yu *et al*, *supra* note 10, at 4.
[141] *Credit Scoring*, ELECTRONIC PRIVACY INFORMATION CENTER (2016), https://epic.org/privacy/creditscoring [https://perma.cc/W94Z-HGWP].

During the process of data transformation, a program may be "designed to discard minor differences that occur in identifiers, such as incorrect digits in a social security number."[142] These errors are often difficult to correct down the line, and credit scorers generally dedicate little time and energy to correcting errors in their datasets.[143] In one example, TransUnion, a major national data broker and CRA, repeatedly mixed the files of two different women – Judy Thomas and Judith Upton – because of similarities in their names, their dates of birth, and their Social Security numbers.[144] TransUnion's mistake meant that a complete stranger's bad debts haunted Judy Thomas for years. TransUnion only corrected the problem after Thomas sued and won a multi-million dollar jury verdict.[145]

Finally, the process of data collection and transformation may lead to problems of transparency. Credit-scoring companies treat their data sources as proprietary trade secrets.[146] In practice, this means that consumers have no realistic means to understand which of the many seemingly inconsequential decisions they make each day could impact their credit ratings, and even less ability to challenge their scores, or test whether the input data are accurate. This problem is likely heightened where a lender relies on thousands of data points and translates these data points into forms that, while intelligible to a computer, are not intelligible to the layperson. Assuming that a diligent applicant could first identify an error among the thousands of entries in the credit scorer's raw data set, it is unlikely that the applicant would have the capacity to prove that the error resulted in a faulty score. As one study puts it, "[a] credit score rests upon [the scorer's] accrual of as many records and cross-correlations of a borrower's financial decisions as possible. [Credit scorers] then reductively collapse the entangled mass of correlations of those

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[142] *Id.*

[143] Frank Pasquale notes that agents at the main credit-reporting agencies reported spending approximately six minutes for each error they were asked to resolve. *See* Frank Pasquale, THE BLACK BOX SOCIETY: THE SECRET ALGORITHMS THAT CONTROL MONEY AND INFORMATION 22 (2015).

[144] *Id.; see also* Matthew Kauffman & Kenneth Gosselin, *Little hope seen for credit report reform*, THE CHICAGO TRIBUNE (May 12, 2003) http://articles.chicagotribune.com/2003-05-12/news/0305120180_1_fair-credit-reporting-act-consumer-disputes-consumers-union [https://perma.cc/2WDW-ZW7N].

[145] *See* Rome Neal, *Mistaken Identity in Credit Report*, CBS NEWS (July 31, 2002), http://www.cbsnews.com/news/mistaken-identity-in-credit-report [https://perma.cc/3X7T-QL48].

[146] *See* Brenda Reddix-Smalls, *Credit Scoring and Trade Secrecy: An Algorithmic Quagmire or How the Lack of Transparency in Complex Financial Models Scuttled the Finance Market*, 12 U.C. DAVIS BUS. L. J. 87 (2011).

activities to a three-digit number, supposedly imbued with comparative social meaning."[147]   Because the data-transformation process likely involves numerous aggregations and combinations of data points, as well as subjective decisions by the data scientist, applicants are likely to have few means to effectively challenge their scores.

iii)   Step 3: developing a final model through analysis of training data and feature selection

Once the data scientist has collected and transformed the corpus of training data, the process of machine learning can begin. But not every input within the training data will prove relevant, and many inputs are likely to be discarded as the system learns what is relevant to the target variable and what is irrelevant. The machine-learning process typically involves an optimization routine that attempts to identify the most significant input variables and the appropriate weights that should be assigned to each. Here, it is helpful to recall Venkatasubramanian's trial-and-error recipe analogy.[148]   In order to develop a final model (the recipe), the data scientist uses computer programs capable of running many successive iterations and analyzing perhaps thousands of combinations of data points in order to identify relevant factors that best correlate to the target variable of interest. This iterative process of identifying relevant inputs and discarding irrelevant inputs is described as "feature selection." Put differently, feature selection refers to the task of choosing a subset of input attributes that are most relevant to the problem and which have the greatest predictive potential.[149]   As the machine-learning process advances, the most predictive features will be assigned greater weights and will be combined into a final model.

As discussed in the prior section, ZestFinance's data-transformation process results in a series of metavariables that may constitute combinations of multiple data points, or may instead represent inferences drawn from particular data points. Once the data are condensed down to a few hundred metavariables for each individual, ZestFinance next undertakes a feature-selection process in which it identifies a

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[147]   Christopher P. Guzelian et al, *Credit Scores, Lending, and Psychosocial Disability*, 95 B.U. L. Rev. 1807, 1815 (2015).

[148]   *See* Section III (A), *supra*.

[149]   Feature selection is an important component of any machine-learning application. Feature selection increases the signal to noise ratio by eliminating irrelevant input variables. *See* Isabelle Guyon & Andre Elisseeff, *An introduction to variable and feature selection*, 3 J. MACHINE LEARNING RES. 1157 (2003).

few significant metavariables that can be used for scoring.[150] ZestFinance's feature-selection process is not uniformly automated, and the company selects the most significant metavariables in one of two ways. In some cases, a data analyst may "curate" or manually determine which metavariables are significant, drawing from past experiences and observations of the applicant pool.[151] In other instances, ZestFinance may rely on statistical algorithms to automatically identify the most significant metavariables.[152] ZestFinance's patent application provides a vague overview of the specific metavariables that go into its credit-scoring models, likely in an effort to retain trade secrecy. As a result, is not possible to determine which of ZestFinance's metavariables have emerged as the most significant, how they are calculated, and whether they are an accurate reflection of creditworthiness.

In the final stage of the ZestFinance scoring process, significant metavariables are fed into "statistical, financial, and other algorithms each with a different predictive 'skill.'"[153] In essence, ZestFinance's final model is a composite of a number of other models. An applicant's final score is an aggregate of the set of scores produced by these models. The patent does not describe how each score is weighted within the final ensemble model.

Once the data scientist has used the transformed training data to develop the final model (or series of models), the model can be deployed to make scoring and lending decisions. At this point, the scorer may not need to collect and input the same amount of data for each new prospective borrower – recall that the machine learning process allows the scorer to discard certain data points that the model determines are irrelevant. However, because creditworthiness is an unstructured problem with no single solution, the credit scorer may also be interested in constantly improving upon the model. Every time the model is deployed to score a new consumer, more data are generated. These new data can be fed back into the machine-learning process, leading to improvements in the model. Information that was previously deemed irrelevant in earlier iterations may take on new meaning as the system continues to learn.

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[150] This is one of the critical components of the scoring process. ZestFinance aggregates different data points for each individual. Not all of these data points are relevant; hence, ZestFinance must determine which of its thousands of input variables or transformations are relevant to ZestFinance's creditworthiness. The resulting variables are called metavariables. *See* U.S. Patent App. No. 14/276,632, *supra* note 75, at ¶¶ 0040-47.

[151] *See id.* at ¶0045.

[152] U.S. Patent App. No. 14/276,632, *supra* note 75, at ¶ 0045.

[153] *Id.* at ¶ 0010.

As the ZestFinance example demonstrates, the manner in which the data scientist develops and refines the final credit-scoring model can potentially create major barriers to transparency and to consumers' ability to challenge scores. The process of data transformation, metavariable development, feature selection, and, finally, the filtering of significant features through multiple models is so complex that even the most sophisticated consumer would likely find it difficult to understand, or to determine whether any inaccuracies in the raw data negatively influenced her final score.

The machine-learning and feature-selection process may also produce models that perpetuate implicit forms of bias and that inadvertently factor in sensitive characteristics such as race. As we will discuss in further detail, longstanding Federal law prohibits lenders from directly taking characteristics such as race or sex into account when making lending decisions.[154] When a credit scorer has thousands of data points to work with, however, the machine-learning process may indirectly consider sensitive characteristics, such as race, even when those characteristics are not directly designated as input values. In many instances, "the attributes that characterize [] subjects [in the dataset] may not be independent from each other."[155] Attributes that are facially neutral may in fact be highly correlated with sensitive characteristics that, by law, cannot be considered.[156] One well-known example is an individual's zip code, which can easily serve as a proxy for a sensitive characteristic like race.[157]

Consumers' use of technology, shopping habits, social-media practices, and other details are likely to vary by race and other sensitive factors. "Thirty percent of whites," for example, "use their mobile phone as their sole Internet connection compared to roughly forty-seven percent of Latinos and thirty-eight percent of blacks."[158] When combined with other information, mobile and Internet usage practices could potentially be used as a proxy for race. If, during the process of

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[154] *See* discussion *infra* Section IV.
[155] Calders & Žliobaitė, *supra* note 96, at 47 (emphasis omitted).
[156] *Id.*
[157] Willy E. Rice, *Race, Gender, "Redlining," and the Discriminatory Access to Loans, Credit, and Insurance: An Historical and Empirical Analysis of Consumers Who Sued Lenders and Insurers in Federal and State Courts, 1950-1995*, 33 SAN DIEGO L. REV. 583, 613, 637-646 (1996).
[158] YU ET AL., *supra* note 10, at 27, *citing* Jessica J. Gonzalez, *Communications Technology Use in Communities of Color: A Presentation to the FCC Technology Transitions Task Force*, NATIONAL HISPANIC MEDIA COALITION, at *9 (Mar. 18, 2013), https://transition.fcc.gov/technologies_transitions_policy_task_force/Panel_2-Jessica_Gonzalez.pdf [https://perma.cc/U9PZ-LMLY].

machine learning, the model learns that race or another sensitive characteristic is highly correlated to credit risk, the model will attach greater significance to proxy variables that can serve as a stand-in for that sensitive characteristic. Even where data miners are careful, "they can still effect discriminatory results with models that, quite unintentionally, pick out proxy variables for protected classes."[159]

The machine-learning and feature-selection process may also produce results that are unfair because an individual's final score may not be made on the basis of the individual's own merits, but rather based on factors the individual coincidentally shares with others that the model deems risky. When a model relies on generalizations reflected in the data, individuals can be victimized by "statistically sound inferences that are nevertheless inaccurate," and which are completely beyond the individual's control.[160] For example, a model that scores individuals on the basis of shared characteristics may penalize "low-income consumers with pristine credit histories . . . simply because they save costs by shopping at low-end stores."[161] Such models may also punish individuals for being members of particular communities or families, or for their affiliations with certain political, religious, and other groups. Kevin Johnson's story provides a good example of this phenomenon in the credit context.[162] What happened to Kevin is not likely an anomaly. In many other areas – from academic admission decisions to the realm of Google search results – big-data tools that judge individuals on the basis of shared characteristics rather than individuals' own merits have been shown to entrench existing bias.[163]

IV. THE INADEQUACIES IN THE EXISTING LEGAL FRAMEWORK FOR CREDIT SCORING

Federal laws already regulate certain aspects of the credit-assessment industry as well as the use of credit scores and reports. The existing legal framework, however, contains multiple gaps and inadequacies. Regulators and consumers

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[159] Barocas & Selbst, *supra* note 93, at 5.

[160] *See id.*, at 18-19.

[161] YU ET AL., *supra* note 10, at 28.

[162] *See* Section II.

[163] *See, e.g.*, Stella Lowry & Gordon Macpherson, *A Blot on the Profession*, 296 BRITISH MED. J. 657 (1988) (finding that an automated system used to sort medical school applicants on the basis of previous admission decisions systematically disfavored racial minorities who were otherwise similarly situated to white applicants); Latanya Sweeney, *Discrimination in Online Ad Delivery*, 56 COMM. ACM 44 (2013) (finding that Google queries with African-American-sounding names were more likely to return advertisements for arrest records than queries using white-sounding names).

may also find it difficult to apply existing laws to many alternative forms of credit assessment because of the new data sources and technologies that these alternative tools use. This part surveys two federal laws that are particularly relevant to the credit-scoring industry, namely the Fair Credit Reporting Act ("FCRA") and the Equal Credit Opportunity Act ("ECOA"). In addition to briefly describing the scope of the FCRA and ECOA regimes and the key requirements the laws impose, this part describes potential problems that both regulators and consumers may face when seeking to apply these laws to non-traditional, big-data credit-scoring models.

A. The Fair Credit Reporting Act (FCRA)

FCRA was enacted in 1970 to serve the dual goals of ensuring fairness in consumer credit reporting, and safeguarding consumers' privacy through limitations on how consumer credit information can be disclosed or used.[164] FCRA furthers these objectives by "requir[ing] that consumer reporting agencies adopt reasonable procedures for meeting the needs of commerce for consumer credit, personnel, insurance, and other information in a manner which is fair and equitable to the consumer, with regard to the confidentiality, accuracy, relevancy, and proper utilization of such information."[165] FCRA also seeks to ensure that consumers can access information about their scores, correct errors, and understand how their personal and credit data are being used by third parties who use it to make credit, employment, and insurance decisions.

While the activities of many alternative credit-scoring companies may trigger FCRA's requirements, a recent study points out that "[i]t is highly unlikely, given the size of the data set and the sources of information, that the companies that provide big data analytics and the users of that data are meeting these FCRA obligations."[166] Providers of alternative credit-assessment tools may also be able to evade FCRA's coverage if, instead of compiling information that is tied to a specific individual, credit scorers aggregate data at the household or neighborhood level, or gather and report data associated with a device or an IP address used by multiple individuals.

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164 *See* Robinson + Yu, *supra* note 11, at 28; *see also generally* S. Rep. No. 91-169 (1969).

165 15 U.S.C. § 1681(b) (2012).

166 *See* Yu ET AL., *supra* note 10, at 5.

i)   Information, entities, and activities governed by FCRA

Whether a particular entity or reporting activity falls under FCRA principally depends on the types of information involved, the actual or expected uses of that information, and whether the information is reported by a "consumer reporting agency" ("CRA"). FCRA governs "consumer reports," which are defined as reports containing "any information . . . bearing on a consumer's credit worthiness, credit standing, credit capacity, character, general reputation, personal characteristics, or mode of living."[167] The information need only satisfy one of these factors, with the practical implication that almost any information about a consumer might qualify.[168]

While the types of information potentially relevant to FCRA are vast, information will not be considered as a consumer report unless it pertains to an "individual,"[169] meaning an "an identifiable person."[170] If a company compiles data on the activities of a household, a neighborhood, and potentially a device or Internet Service Protocol ("ISP") address, the company's reports may not be subject to FCRA's requirements.[171] Courts have held, for example, that reports containing information on individuals who share a common surname are not governed by FCRA because the reports do not pertain to single individuals.[172] One court has suggested that reports pertaining to a house or property, and not strictly to the property's owner, may fall outside of FCRA.[173] Reports that purport to strip out a consumer's personally identifying information and assign an anonymous customer ID to the information could also side-step this requirement,[174] despite

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[167]   15 U.S.C. § 1681a(d)(1) (2012).

[168]   National Consumer Law Center, *Fair Credit Reporting* § 2.3.4.1 (8th ed. 2013), www.nclc.org/library [https://perma.cc/8RKG-JHGW]; *see also* Trans Union Corp. v. Fed. Trade Comm'n, 245 F.3d 809 (D.C. Cir. 2001).

[169]   15 U.S.C. § 1681a(c) (2012).

[170]   McCready v. EBay, Inc., 453 F.3d 882 (7th Cir. 2006) (information pertaining to an anonymous computer username does not qualify under definition of "consumer report").

[171]   *See* Robinson + Yu, *supra* note 11, at 17.

[172]   Fiscella v. Intelius, Inc., 2010 WL 2405650 (E.D. Va., June 10, 2010).

[173]   Fuges v. Southwest Fin. *Serv., Ltd.*, 707 F.3d 241, 253 (3d Cir. 2012) (finding that it was not unreasonable for the defendant to interpret the FCRA's definition of a consumer report as excluding information about encumbrances on a property, even if the property was owned by an identifiable consumer).

[174]   For example, Verizon assigns a "Unique Identifier Header" ("UIDH") to each of its mobile customers, allowing the company to track users across devices, logging details on browsing habits, geolocation, and other information. *See* VERIZON   WIRELESS,   https://www.verizonwireless.com/support/unique-identifier-header-faqs [https://perma.cc/Z77M-QK3V]. The online advertising company Turn also recently came under public scrutiny for devising so-called

the fact that such identifiers may easily be linked back to a particular consumer.[175] While the FTC has taken the position that information, even if not tied to a consumer's name, may qualify as a consumer report if it could be "reasonably [] linked to the consumer,"[176] it remains to be seen whether de-identification methods can be used to circumvent FCRA's requirements.

Application of FCRA further depends on whether the information an entity collects and sells constitutes a "consumer report" under the Act. In order to qualify as a "consumer report," the information must be "used or expected to be used or collected" to serve as "a factor in establishing the consumer's eligibility for" three purposes: credit, insurance, and employment.[177] The origin and nature of the information thus make no difference to FCRA coverage; applicability turns on the purposes for which such information is collected, as well as actual or likely end-uses for the information.[178] The individual or entity supplying the information need not have proof that the information will be used for a covered purpose; it is enough "if, in the usual course of events, one would expect that one of the uses of a report would be a listed one."[179] As big-data models expand the types of information analyzed for credit decisions, factors not previously considered as falling within the scope of FCRA, such as geolocation and online browsing history information, may qualify under the Act.

FCRA's final definitional element further circumscribes its scope, making clear that information that nominally qualifies as a "consumer report" will not trigger the Act's requirements unless it is supplied by an entity meeting the definition of a "consumer reporting agency"("CRA").[180] A CRA is defined as "[a]ny person which, for monetary fees, dues, or on a cooperative nonprofit basis . . . [r]egularly engages in whole

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"zombie cookies" that employ a Verizon user's UIDH to "to respawn tracking cookies that users have deleted." Julia Angwin & Mike Tigas, *Zombie Cookie: The Tracking Cookie That You Can't Kill*, PROPUBLICA (Jan. 14, 2015), http://www.propublica.org/article/zombie-cookie-the-tracking-cookie-that-you-cant-kill [https://perma.cc/7H5W-JKY4]. Turn reportedly suspended the use of its "Zombie Cookies" in response to public criticism. *Id.*

175 *See* Angwin & Tigas, *supra* note 174.
176 FEDERAL TRADE COMMISSION, *40 Years of Experience with the Fair Credit Reporting Act: An FTC Staff Report with Summary of Interpretations*, *reprinted in* National Consumer Law Center, *Fair Credit Reporting*, at Appx. D, Part V (8th ed. 2013), www.nclc.org/library [https://perma.cc/8RKG-JHGW].
177 15 U.S.C. § 1681a(d)(1) (2012).
178 *Fair Credit Reporting*, *supra* note 168, at § 2.3.5.1.
179 *Id.* at § 2.3.5.3, *citing Ippolito v. WNS, Inc.*, 636 F. Supp. 471 (N.D. Ill. 1986) and Belshaw v. Credit Bureau of Prescott, 392 F. Supp. 1356, 1359 (D. Ariz. 1975).
180 15 U.S.C. § 1681a(f) (2012).

or in part in the practice of assembling or evaluating consumer credit information or other information on consumers" for the purpose of "furnishing consumer reports to third parties."[181] Based on this final requirement, many collection and reporting activities may fall outside of FCRA's bounds. For example, a lender that develops its own mechanisms for collection and data analytics will not trigger FCRA as long as it does not resell that information for further use in the credit, insurance, or employment context.[182] The definition of CRA may also create a loophole for big-data companies that segment their internal operations and wall off any credit-reporting activities from other activities, such as targeted marketing. As the National Consumer Law Center points out, "one division of a corporation can collect consumer reports, while another collects business reports. As long as the business reports are not derived from a consumer report, but are independently collected solely for a business purpose, that division would not act as a CRA."[183]

A number of companies that currently collect and compile the types of information increasingly used to assess creditworthiness or to make decisions under other listed FCRA purposes have attempted to evade the Act's application by disclaiming any responsibility for how the information is used. For example, Intelius, a major data broker, declares on its website that it "is not a consumer reporting agency as defined in the [FCRA]," and that those using its reports shall not do so for any of the purposes set out in the FCRA.[184] The FTC has cracked down on certain data brokers who rely on disclaimers to disavow responsibilities under FCRA,[185] however, there is evidence that these practices remain widespread among many data brokers.[186]

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[181] 15 U.S.C. § 1681a(f) (2012).

[182] It should be noted that the FCRA also specifically excepts actors that only acquire data "first-hand" from consumers, *see* 15 U.S.C. § 1681a(d)(2)(A)(i) (2012), a flexibility that may have particular importance for online lenders that use detailed applications. *See also* Robinson + Yu, *supra* note 11, at 28.

[183] *Fair Credit Reporting, supra* note 168, at § 2.5.2.

[184] *See* YU ET AL., *supra* note 10, at 26 (setting out examples of data broker disclaimers).

[185] *See, e.g.*, Consent Decree, *United States v. Spokeo, Inc.*, No. CV12-05001 MMM (C.D. Cal., June 7, 2012).

[186] *See* YU ET AL., *supra* note 10, at 26. For instance, Spokeo still maintains a disclaimer on its website even after it was subject to a major FTC enforcement action. *See* SPOKEO, *Terms of Use*, http://www.spokeo.com/terms-of-use [https://perma.cc/J9X3-KK9H].

ii)   Key FCRA requirements and limitations on use of consumer reports

Out of concern for consumers' privacy, once information qualifies as a "consumer report," FCRA only permits its use for certain permissible purposes;[187] for instance, use in connection with a consumer credit transaction.[188]   Consumer reports cannot be sold for non-permissible purposes, such as targeted marketing.[189] A CRA must maintain reasonable safeguards to ensure information is used permissibly, and must refuse to furnish a report if it has reason to believe the recipient intends to do otherwise.[190]

CRAs must also use reasonable procedures to guarantee the accuracy of information in consumer reports.[191] Not only must the information in a report be literally true, it also must not be misleading or incomplete.[192] When a lender takes an adverse action on a consumer's application based upon information contained in a consumer report, FCRA obligates the lender to notify the consumer of the adverse action, identify the CRA that provided the report, and provide instructions on how the consumer can obtain the information in the report.[193] The consumer has the further right to request and obtain information in the report,[194] as well as to challenge the accuracy of the information.[195]

In the traditional credit-scoring context, FCRA's transparency mechanisms have provided an important, albeit imperfect, safeguard against abuses and mistakes. These measures, however, may not be effective in the alternative credit-scoring context, where the data points collected and used are increasingly vast and where scoring companies may be

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[187] 15 U.S.C. § 1681b(a) (2012); Cole v. U.S. Capital, 389 F.3d 719 (7th Cir. 2004); Trans Union L.L.C. v. Fed. Trade Comm'n, 295 F.3d 42, 49 (D.C. Cir. 2002).

[188] *See* 15 U.S.C. §1681b(a) (2012).

[189] *See* Trans Union Corp. v. FTC, 245 F.3d 809, 812-16 (D.C. Cir. 2001) (confirming the FTC's finding that lists containing the names and address of individuals who have auto loans, department store credit cards, or mortgages, qualified as consumer reports under the FCRA, and that the sale of such lists for target marketing purposes was a violation of the Act).

[190] *Fair Credit Reporting, supra* note 168, at § 7.1.2.1 (citing 15 U.S.C. § 1681e(a) (2012)); Levine v. World Fin. Network Nat'l Bank, 437 F.3d 1118 (11th Cir. 2006).

[191] 15 U.S.C. § 1681e(b) (2012).

[192] *See Fair Credit Reporting, supra* note 168, at § 4.2.3.

[193] 15 U.S.C. § 1681m(a) (2012); *see also Fair Credit Reporting, supra* note 168, at § 3.3.6.

[194] 15 U.S.C. § 1681g (2012).

[195] 15 U.S.C. § 1681i(a)(2012).

taking steps to circumvent FCRA's definitional scope.[196] Consumer advocacy groups have already raised concerns that "compliance with [the FCRA's] notice requirement is sparse with non-traditional consumer reports."[197] Given that non-traditional scoring models rely on thousands of pieces of information collected from multiple sources, it will likely prove extremely difficult for consumers to identify and challenge inaccuracies in the raw data,[198] and even more difficult to contest inferences drawn from analysis of the raw data points. By placing the burden of ensuring accuracy on the shoulders of individual consumers, FCRA's protections may prove increasingly ineffective as scorers adopt alternative big-data models.

iii) Key issues and challenges not addressed by FCRA

While FCRA limits uses of information in consumer reports and provides procedural safeguards to correct mistakes, it does not limit the types of information that can be used to score credit, aside from certain forms of outdated criminal records and financial records.[199] As a consequence, consumers may have few guideposts allowing them to understand what stands behind a credit decision and what steps they can take to improve their scores. Although "a similar critique is certainly true of FICO and other traditional credit scores," such concerns are heightened in the case of big-data alternative credit scoring, where consumers have practically zero notice as to what information is being collected about their behavior, and how it is being used.[200]

To the extent that FCRA requires alternative credit-scoring companies to provide consumers with the opportunity to access and correct information about them, it may prove practically impossible for consumers, when dealing with big-data scoring systems that potentially integrate thousands of variables, to verify the accuracy of their scores and reports or

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[196] For example, the FCRA does not apply to companies that collect and maintain their own data on consumers, and use it internally rather than selling it. *See* 15 U.S.C. § 1681a(d)(2)(A)(i) (2012). As a practical consequence, online lenders that acquire their information first-hand from consumers or through automated web-crawling will not be subject to the FCRA. *See* Robinson + Yu, *supra* note 11, at 28.

[197] YU ET AL., *supra* note 10, at 24; *see also* Persis S. Yu & Sharon M. Dietrich, *Broken Records: How Errors by Criminal Background Checking Companies Harm Workers and Businesses*, NCLC (Apr. 2012), www.nclc.org/issues/broken-records.html [https://perma.cc/SVY9-X24R].

[198] *See* YU ET AL., *supra* note 10, at 25.

[199] *See* 15 U.S.C. § 1681c (2012).

[200] YU ET AL., *supra* note 10, at 20.

to challenge decisions based on alternative models. FCRA's transparency and reporting requirements place the burden on individual consumers to identify and contest errors and inaccuracies in the data that may impact upon their final scores. This system is likely to prove unworkable for big-data tools.

While the Equal Credit Opportunity Act ("ECOA"), discussed below, prohibits lenders from considering sensitive factors such as race when making lending decisions,[201] neither law expressly prohibits the consideration of many data points that are facially unrelated to consumers' financial practices and that may also serve as proxies for immutable or sensitive characteristics. FCRA also "does not explicitly require credit scores to be predictive of creditworthiness" at all,[202] meaning that FCRA cannot prevent scorers from using big-data machine-learning tools to predict other outcomes, such as consumer vulnerability.

B. The Equal Credit Opportunity Act (ECOA)

Congress enacted ECOA in 1974 to prohibit creditors from discriminating against credit applicants on the basis of sensitive characteristics such as race, religion, national origin, sex, or marital status.[203] Since its enactment, ECOA and its accompanying Regulation B have served as the primary vehicle for individuals and classes of consumers to challenge lending decisions and policies that are either patently discriminatory, or that lead to discriminatory results. Plaintiffs have two principal options to bring an ECOA claim: they can either allege disparate treatment by showing that they were specifically singled out and treated unfavorably on the basis of some sensitive characteristic such as race, or they can allege disparate impact, by showing that a facially neutral lending policy resulted in less favorable terms for members of a protected class when compared with other similarly situated borrowers.

The existing ECOA framework governs lending decisions made using big-data machine-learning tools just as it does lending decisions using traditional tools. Borrowers are likely to find, however, that it is much more difficult to make the case for either disparate treatment or disparate impact

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[201] *See* subsection B, *infra.*

[202] YU ET AL., *supra* note 10, at 20.

[203] 15 U.S.C. § 1691(a)(1) (2012); *see also, e.g.*, 12 C.F.R. § 1002.1 (2016) ("The purpose of this part is to promote the availability of credit to all creditworthy applicants without regard to race, color, religion, national origin, sex, marital status, or age. . . ."); *Treadway v. Gateway Chevrolet Oldsmobile Inc.*, 362 F.3d 971, 975 (7th Cir. 2004).

when a lender justifies its decisions on a credit-scoring process that uses sophisticated algorithms and thousands of data points. There are several reasons for this. *First*, to the extent that a lender wishes to implement a lending policy that deliberately singles out members of a particular racial, ethnic, or other group, the lender likely can employ facially-neutral proxy variables in its scoring model as stand-ins for characteristics like race. *Second*, to the extent that lending decisions accord less favorable treatment to a protected class, the lender may be able to claim that its "objective," data-driven, modeling processes are proof that the disparate impact is grounded in business necessity.

i)   Entities and activities governed by ECOA

ECOA governs the activities of creditors and protects against discrimination in credit transactions. ECOA's definition of "creditor" encompasses three groups: 1) "[a]ny person who regularly extends, renews, or continues credit;" 2) "any person who regularly arranges for the extension, renewal, or continuation of credit;" or 3) "any assignee of an original creditor who participates in the decision to extend, renew, or continue credit."[204] ECOA regulations further clarify that any "person who, in the ordinary course of business, regularly participates in a credit decision, including setting the terms of the credit," can constitute a creditor under the Act.[205]

ECOA defines the term "credit transaction" as "every aspect of an applicant's dealings with a creditor regarding an application for credit or an existing extension of credit."[206] ECOA's scope of coverage thus includes, but is not limited to, "information requirements; investigation procedures; standards of creditworthiness; terms of credit; furnishing of credit information; revocation; alteration, or termination of credit; and collection procedures."[207]

These definitions are likely to capture the activities of credit scorers even if they merely provide credit scores or credit-assessment tools, but do not make the ultimate call on whether to grant a loan. Companies that develop credit-risk modeling tools arguably "participate[] in credit decision[s]" by developing "standards of creditworthiness" even when they merely furnish the models that lenders ultimately deploy to make lending decisions. FTC Chairwoman Edith Ramirez has warned, however, that ECOA likely does not reach entities that

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[204] 15 U.S.C. § 1691a(e) (2012).
[205] 12 C.F.R. § 202.2(l) (2016).
[206] 12 C.F.R. § 202.2(m) (2016).
[207] *Id.*

use scoring tools to determine whether to solicit vulnerable individuals with advertisements for subprime or other less-favorable credit products.[208]   ECOA thus may not serve as an effective check on companies that use of big-data credit-scoring tools to unfairly target minority consumers with products like payday loans.

ii)   Challenging discrimination under ECOA

ECOA only prohibits discrimination on a limited number of grounds, namely "race, color, religion, national origin, sex, or marital status."[209]   ECOA further prohibits creditors from treating consumers differently because they "derive[] [income] from any public assistance program."[210] The scope of ECOA's discrimination protections is potentially limiting.   For instance, by its terms ECOA does not clearly prohibit discrimination on the basis of a consumer's sexual orientation.   While some courts have interpreted ECOA's prohibition on sex discrimination as encompassing claims where an individual was denied access to credit because he or she did not comply with the lender's expectations regarding gender norms,[211] consumers may find it difficult to challenge lender discrimination based on sexual orientation.

Proving a violation of ECOA is burdensome, and the use of highly complex big-data credit-scoring tools may only exacerbate that difficulty.   In order show discrimination under ECOA, a plaintiff must either demonstrate "disparate treatment" by proving that the lender based its lending decision on "a discriminatory intent or motive,"[212] or "disparate treatment," by showing that the lender's practices or decisions have had a "disproportionately adverse effect on minorities."[213]

While reliance on big-data scoring tools may lessen the frequency of instances of disparate treatment by decreasing the influence of individual loan-officer discretion on lending decisions, as Barocas and Selbst point out, tools that employ

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[208]   Edith Ramirez, Chairwoman, FTC, *Protecting Privacy in the Era of Big Data*, Remarks Before the International Conference on Big Data from a Privacy Perspective, at *5 (June 10, 2015), *available as* 2015 WL 3824154.

[209]   15 U.S.C. § 1691(a)(1) (2012).

[210]   15 U.S.C. § 1691(a)(2) (2012).

[211]   *See, e.g.*, Rosa v. Park W. Bank & Trust Co., 214 F.3d 213, 215 (1d Cir. 2000) (recognizing that "prohibited bases of discrimination under the ECOA do not include [] sexual orientation," but finding violation of ECOA sufficiently alleged where plaintiff discrimination because his "attire did not accord with his male gender").

[212]   *Cf.* Ricci v. DeStefano, 557 U.S. 557, 557 (2009) (construing the disparate treatment test in the context of an employment discrimination suit under Title VII of the Civil Rights Act of 1964).

[213]   *Cf. id.*

thousands of data points and complex models could also potentially be used to mask overtly discriminatory policies.[214] Perhaps more likely, however, big-data tools may perpetuate existing, systemic forms of discrimination. As discussed above, machine-learning tools may foment unintentional discrimination if they define target variables in a manner that encodes existing bias, rely on inaccurate sample data, or permit the use of proxy variables for sensitive characteristics such as race.

A consumer's best option to combat such unintentional forms of discrimination under ECOA is likely to allege disparate impact. Under current law, however, this is a difficult showing to make. ECOA's text makes no mention of disparate impact analysis. The Supreme Court has not yet considered whether plaintiffs can bring disparate-impact claims under ECOA, though circuit courts have consistently held that such claims are available.[215] ECOA's implementing regulations make express reference to disparate impact, stating that ECOA's "legislative history [] indicates that the Congress intended" to allow "effects test" claims akin to those permitted in the employment context.[216]

The Supreme Court recently examined disparate-impact claims in the context of the Fair Housing Act (FHA) and affirmed that such claims remain viable under the FHA and similar antidiscrimination laws whose "text refers to the consequences of actions and not just to the mindset of actors, and where that interpretation is consistent with statutory purpose."[217] In *Inclusive Communities Project, Inc.*, the Supreme Court also appears to have announced a more stringent standard for plaintiffs who wish to show disparate impact, cautioning that "disparate impact liability must be limited so employers and other regulated entities are able to

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[214]   Barocas & Selbst, *supra* at note 93, at 22 ("Data mining could also breathe new life into traditional forms of intentional discrimination because decision-makers with prejudicial views can mask their intentions by exploiting" various machine learning techniques.).

[215]   *See, e.g.*, Golden v. City of Columbus, 404 F.3d 950, 963 (6th Cir. 2005) (noting that Supreme Court has not yet decided whether disparate impact cognizable under ECOA, but reasons that statute seems to permit disparate impact analysis).

[216]   12 C.F.R. § 202.6(a) (2016), at n.2 ("Congress intended an 'effects test' concept, as outlined in the employment field by the Supreme Court in the cases of *Griggs v. Duke Power Co.*, 401 U.S. 424 (1971), and *Albemarle Paper Co. v. Moody*, 422 U.S. 405 (1975), to be applicable to a creditor's determination of creditworthiness").

[217]   Texas Dep't of Housing & Cmty. Affairs v. Inclusive Communities Project, Inc., 135 S. Ct. 2507, 2518 (2015).

make the practical business choices and profit-related decisions that sustain a vibrant and dynamic free-enterprise system."[218]

Historically, in order to make a prima facie case of disparate impact, plaintiffs were required to show three things: 1) a specifically identifiable practice or policy; 2) a statistically significant disparity in treatment between a protected group and other groups; and, 3) a causal link between the disparity and the practice or policy.[219] It has never been sufficient for a plaintiff to simply show an imbalance between a protected group and a non-protected group, no matter how stark.[220] In *Inclusive Communities Project, Inc.,* the Supreme Court signaled that plaintiffs face an increasingly stringent set of hurdles when identifying the policy or practice that causes the disparate impact. According to the Court, "a one-time decision may not be a policy at all."[221] The Court also indicated that plaintiffs might face a heightened standard for causation, noting that "[i]t may also be difficult to establish causation" where "multiple factors" stand behind the challenged decision or policy.[222] The Court also stated that a "robust causality requirement," will "protect defendant from being held liable for racial disparities they did not create."[223] Although it is not clear how the Court's reasoning will play out in a credit-scoring context, the Court's emphasis on "robust causality" raises the possibility that credit scorers may be able to avoid disparate impact liability if they can show that their models merely reflect and reproduce existing forms of systemic bias against minorities.

Assuming that a plaintiff can make a prima facie case of disparate impact, the defendant can still avoid liability if the defendant can make a showing of "business necessity" by "stat[ing] and explain[ing] [a] valid interest served" by the challenged policy.[224] In order to prove "business necessity," the defendant need not show that the challenged policy or practice was indispensable to its objective, but only that the policy was "related" to its objective or business goals.[225] If the defendant

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[218] *Id.* at 2518.

[219] *See, e.g.,* Wards Cove Packing Co. v. Atonio, 490 U.S. 642, 657-58 (1989) (superseded by statute on other grounds) ("As a general matter, a plaintiff must demonstrate that it is the application of a specific or particular employment practice that has created the disparate impact under attack.").

[220] *See, e.g., id.*

[221] Inclusive Communities Project, Inc., 135 S. Ct. at 2523.

[222] *Id.* at 2523-24.

[223] *Id.* at 2523.

[224] *Id.* at 2522, 2512; *see also, e.g.,* Ricci v. DeStefano, 557 U.S. 557, 587 (2009).

[225] *See, e.g.,* Ricci, 557 U.S. at 578 ("the 'touchstone' for disparate-impact liability is the lack of 'business necessity': If an employment practice which operates to exclude minorities cannot be shown to be related to job performance, the practice is prohibited." (internal quotations omitted)).

shows business necessity, the burden shifts back to the plaintiff to offer a policy or practice that would be equally effective in meeting the defendant's goals, but that would not produce a disparate impact.[226]

There are few examples of past cases in which plaintiffs have challenged automated credit-scoring tools under ECOA using the disparate impact theory.[227] As the above analysis suggests, the exacting standards set out by the Supreme Court will likely make it extremely difficult for future plaintiffs to do so, particularly when dealing with complex big-data tools that employ thousands of data points. Credit scorers have trade secrecy on their side; at present, consumers and regulators have no practical way to dig into the models to understand what drives lending decisions, and determine whether the target variables and training data are impacted by implicit forms of bias. Assuming that a plaintiff could, absent access to the models and data, pinpoint policies that lead to discriminatory outcomes, the plaintiff will still likely lose unless she can offer a non-discriminatory alternative option to model creditworthiness. Put simply, unless consumers have the ability to pull back the curtain and understand how big-data credit-scoring tools work, scorers and lenders may be able to perpetuate systemic bias with relative impunity.

V. THE CHALLENGES OF ALTERNATIVE CREDIT-SCORING AND A LEGISLATIVE FRAMEWORK FOR CHANGE

This article has attempted to describe how big-data and machine-learning techniques are changing the credit-scoring industry, as well as the difficulties that regulators and consumers will likely face when they seek to apply existing federal laws like FCRA and ECOA to alternative credit-scoring tools. As the above discussion indicates, big-data credit-scoring tools potentially present four major challenges, namely: 1) insufficient transparency, 2) input data that are potentially inaccurate, 3) the potential for biased and discriminatory scoring, and 4) the risk that these tools will be used to target vulnerable consumers. These challenges are all somewhat

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[226] *See, e.g.*, Watson v. Fort Worth Bank & Trust, 487 U.S. 977, 998 (1988).

[227] Beaulialice v. Fed. Home Loan Mortgage Corp., No. 8:04-CV-2316-T-24-EA, 2007 WL 744646 (M.D. Fla. Mar. 6 2007), offers a rare example of a challenge to a credit-scoring algorithm under the disparate impact theory. Unfortunately, *Beaulialice* provides little insight into how a court might view a disparate impact claim in the credit-scoring setting as the case was dismissed on the ground that the plaintiff's claims were barred by the doctrine of "unclean hands." *Id.*

dependent on one another, meaning that the adequacy a solution to one challenge may rest upon the effectiveness of the solutions to the other challenges. For example, absent an effective mechanism to solve the transparency problem, regulators and consumers will arguably have difficulty determining whether a particular scoring system relies on data points that operate as proxies for sensitive features such as race, or whether the scoring system targets vulnerable individuals. In order to challenge instances of implicit bias in a model, regulators will need to understand how the model's target value is defined, what data points are used to score, and what the model's most important features are. Similarly, if lenders are permitted to use models that are designed to identify consumers that are financially vulnerable and more susceptible to predatory products, this could further entrench discriminatory lending patterns down the road. Any legislative solution that only addresses some, but not all, of the challenges posed by big-data credit-scoring tools will be inadequate.

We propose that each of these four challenges can be addressed through legislation that is designed to complement the existing legal framework. To that end, we offer a model bill – the *Fairness and Transparency in Credit Scoring Act* ("FaTCSA") – that could be enacted at either the federal or state level.[228] This model legislation was developed as part of a collaborative effort between data scientists at the Massachusetts Institute of Technology and legal scholars at the Georgetown University Law Center. Although the FaTSCA is designed with alternative credit-scoring tools in mind, it is broad enough in scope to encompass even traditional credit-scoring tools. In this section, we briefly summarize each of the four challenges posed by big-data credit scoring, and describe the FaTSCA's proposed solutions to those challenges.

A. Existing transparency rules are inadequate

As discussed above, big-data scoring systems like those used by ZestFinance are currently treated as protected trade secrets, thereby making it extremely difficult for consumers to understand what impacts their scores and what steps they should take to responsibly improve their access to credit. While we do not suggest that traditional credit-scoring models are perfect examples of transparency, the transparency problem is less acute for these tools because they employ only a

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[228] *See infra* p. 202, Julius Adebayo, Mikella Hurley & Taesung Lee, *Model Fairness and Transparency in Credit Scoring Act (FaTCSA)*. The Model FaTSCA is reproduced with permission of its authors. As currently drafted, the Model FaTSCA has been optimized for enactment at the state level.

handful of features that are intuitively related to consumer financial behavior, and are publically-regarded–whether rightly or wrongly–as setting consistent guideposts for defining creditworthiness. Non-traditional scoring tools, by contrast, use many factors that lack an intuitive connection to financial behavior. Consumers may also be unaware that certain of these factors are being tracked, let alone used for credit decisions. The secrecy surrounding credit scoring is likely to make it exceedingly difficult for consumers and regulators to determine whether a particular model employs inaccurate data or treats as significant sensitive features such as race. However, under existing federal laws like FCRA and ECOA, consumers and regulators are responsible for producing proof of both problems.

The Model FaTCSA proposes to address the transparency deficit by requiring that all developers and users of credit-scoring and assessment tools make routine disclosures regarding the classes and categories of data that they collect, the sources of this data, the collection methods used, and the particular data points (or combinations of data points) that individual models treat as significant.[229] These disclosures must be updated routinely so that consumers and regulators can remain apprised of changes that affect credit access.[230] Although these disclosures would not necessarily provide direct or conclusive evidence that a particular model uses inaccurate input data or relies on proxies for sensitive characteristics, enhanced reporting on data categories, sources, and significant features will arguably better enable consumers and regulators to identify those scoring tools and models that deserve closer scrutiny. The FaTCSA's transparency rules would also allow consumers to gain a basic understanding of how they are scored so that they can responsibly improve their access to credit.

We anticipate that critics of the FaTCSA's transparency proposals may raise concerns about the potential that consumers will learn how to "game" the scoring system once consumers find out what features are most significant to a particular model. While we agree that enhanced transparency could benefit consumers by allowing them to adapt their behavior to new rules, we maintain that the risk that this will lead to widespread "gaming" of the system is likely limited, and is heavily outweighed by the need to offer consumers clear guideposts to navigate the credit system. If a credit-scoring system defines certain actions or characteristics as "responsible," and others as "irresponsible," consumers should

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[229] *See id.* at § 3(a), p. 204.
[230] *See id.* at § 3(b), p. 204.

be able to change their behavior to emulate the responsible behaviors. Past experience dealing with traditional scores such as FICO supports this view. Few would argue that a consumer is "gaming" the FICO system when she diligently pays off her credit card balance at the end of the month, even if she does so with the knowledge that this behavior will ultimately improve her credit score.

Critics may also question whether the FaTCSA's transparency proposals will negatively impact innovation by allowing competitors to reverse-engineer a particular scorer's model. While total trade secrecy could allow certain scorers to maximize their business advantage, we maintain that this interest does not outweigh the need to ensure that consumers are informed and can challenge inaccurate, biased, and potentially predatory models. The FaTCSA's transparency rules are designed to be selective, and to allow credit scorers to maintain a substantial degree of trade secrecy. While some experts have demanded that credit scorers disclose everything about their models, including their formulas and programing source code,[231] the FaTCSA seeks to strike a balance between encouraging innovation and preserving transparency.

B. The burden of ensuring accuracy should not fall to the consumer

Existing laws like the FCRA establish basic accuracy requirements for the data used in credit-assessment tools, however consumers bear the burden of identifying and disputing inaccuracies.[232] As stories like that of Judy Thomas indicate, credit scorers may not be striving to achieve high levels of accuracy with regard to their input data because the costs of doing so outweigh the marginal financial benefits of that increased accuracy. FCRA's accuracy requirements appear to offer inadequate incentives to increase data accuracy, even in the conventional credit-scoring context where scorers are dealing with fewer types and sources of data. As credit-assessment tools integrate more data points, many of which may be difficult for consumers to verify or dispute, the law should shift the burden of accuracy to the shoulders of the credit scorers themselves.

The Model FaTCSA would require all developers and users of credit assessment tools to maintain rigorous standards of accuracy, conduct regular reviews of their data, and

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[231] *See* Danielle Keats Citron & Frank Pasquale, *The Scored Society: Due Process for Automated Predictions*, 89 WASH. L. REV. 1, 25 (2014).

[232] *See* 15 U.S.C. § 1681i(a) (2012).

regularly self-certify that they comply.[233] The FaTCSA would not only require that scorers ensure that the raw data points they use are accurate, it would also obligate scorers to have safeguards in place to make certain that all data points are verifiable and traceable to the individual consumer, such that similarities in names, social security numbers, and other identifiers do not lead to mistakes that plague responsible borrowers.[234] The option for periodic inspections and audits would allow regulators to determine whether the scorers' certifications are an accurate reflection of scorers' actual practices and efforts to improve accuracy.[235] The FaTCSA also proposes stiff penalties for inaccuracies, and would empower both regulators and citizens to police non-compliance.

C. Better tools are needed to detect and prevent discrimination by proxy

While federal laws offer some existing protections against discriminatory credit scoring, the current regime is likely to be insufficient to address the unique concerns raised by big-data scoring tools. Neither FCRA nor ECOA place substantial limits on the types of data used in credit scoring.[236] As a consequence, there is little to prevent scoring tools from inadvertently using innocuous data points as proxies for sensitive attributes such as race. Additionally, although ECOA prohibits lenders from basing lending decisions on factors such as race, ethnicity, and sex,[237] it omits other sensitive characteristics such as sexual orientation. Finally, while ECOA allows plaintiffs to bring both disparate-treatment and disparate-impact claims, courts have interpreted these tests stringently, and place an extraordinary burden on plaintiffs to prove either deliberate discrimination, or to show that an unjustified, uniform policy has led to less-favorable treatment of certain groups. [238]

The Model FaTCSA would address these problems by shifting the burden to the developers and users of credit-scoring tools to ensure that their tools do not score consumers based upon immutable characteristics or certain sensitive

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[233]   *See infra* pp. 206-207, Model FaTSCA, at §§ 4(d), 4(g), 5.
[234]   *See id.* at § 4(d), p. 206.
[235]   *See id.* at § 6, pp. 207-208 .
[236]   *See, e.g.*, 15 U.S.C. § 1681c (2012).
[237]   *See* PATRICIA A. McCOY, BANKING LAW MANUAL: FEDERAL REGULATION OF FINANCIAL HOLDING COMPANIES, BANKS AND THRIFTS § 8.02[1][a][ii] (2d ed. 2015) ("With respect to marital status, age, the receipt of public assistance benefits and immigration status, however, Congress deemed it legitimate to take those factors into account under certain circumstances").
[238]   *See supra* Section IV(B)(ii).

affiliations, unless such scoring is otherwise permitted under federal law.[239] The FaTCSA addresses the potential problem of proxy-based discrimination by prohibiting the use of models that "treat as significant any data points or combinations of data points that are highly correlated" to sensitive characteristics and affiliations.[240] The FaTCSA also requires that scoring models be based on empirically-sound sample data in order to avoid situations where the training dataset used during the machine-learning and feature-selection stages does not produce a model that inadvertently favors particular groups.[241] Credit scorers must validate and certify that they have repaired their data and have developed their models such that they avoid discrimination by proxy.[242] The FaTSCA does not prescribe particular methodologies that scorers must use to prevent proxy-based discrimination, but rather mandates that scorers adhere to "industry best practices."[243] The FaTCSA thus encourages the data scientists that develop these scoring systems to keep pace with new proposals and developments in the area of algorithmic accountability.[244]

D. Credit-assessment tools should not be used to target vulnerable consumers

Given that big-data scoring tools are becomingly increasingly prevalent in the online payday-lending industry,[245] there is a risk that these sophisticated tools will be used to identify vulnerable individuals who will be most susceptible to predatory loan products. This risk demands an immediate legislative response. At present, no federal law requires that credit-assessment tools be designed to predict a consumer's

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[239] *See infra* pp. 206-207, Model FaTSCA, at § 4(b)-(c). Credit scorers would be permitted, for example to consider a borrower's age pursuant to the limitations already imposed by ECOA. *See* McCOY, *supra* note 237, at § 8.02[1][a][ii].

[240] *See infra*, pp. 206-207, Model FaTSCA, at § 4(b)-(c).

[241] *See id.* at 407, at § 4(e).

[242] *See id.* at § 4(g).

[243] *See id.*

[244] Data scientists and lawyers have already proposed technical solutions to such problems as discrimination by proxy. One such group of experts, for example, proposes a method that could be used to "repair" training datasets at the outset to eliminate implicit bias, thereby avoiding the risk that factors like race or gender will be weighted in a final scoring model. *See* Michael Feldman et al., *Certifying and Removing Disparate Impact*, PROC. 21TH ACM SIGKDD INT'LL CONF. KNOWLEDGE DISCOVERY & DATA MINING 259-68 (2015); Ifeoma Ajunwa et al., *Hiring by Algorithm: Predicting and Preventing Disparate Impact* (Mar. 10, 2016), http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2746078 [https://perma.cc/734W-9AS7].

[245] *See* Section III(B).

actual creditworthiness. Although certain predatory lending practices themselves may be prohibited, there is no requirement that credit-scoring models consider the impact that a loan product could have on a consumer's future financial stability. The Model FaTCSA would require that all credit scores and credit assessment tools be predictive of creditworthiness, defined as a "consumer's likelihood of repaying a loan or debt and the consumer's ability to do so without risking serious harm to the consumer's financial stability."[246] To the extent that a credit-scoring tool is designed to account for other considerations such as a lender's profit margins, these considerations cannot override the imperative of creditworthiness.

VI. CONCLUSION

Big-data credit-scoring tools may, as their proponents claim, emerge as a way to ensure greater efficiency in underwriting while expanding access to the underbanked and to historically neglected groups. But this zeal to "build a better mousetrap" must be tempered against its possible perils. As stories like Kevin Johnson's illustrate, bigger data does not necessarily produce better decisions. Because of the life-altering consequences that can flow from a faulty or unfair credit score, regulators must ensure that innovators proceed responsibly and have strong legal incentives to ensure that their scoring decisions are transparent, accurate, unbiased, and fair.

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[246] *See infra* p. 205, Model FaTSCA, at § 4(a).

VII. ANNEXES

ANNEX 1: THE MODEL FAIRNESS AND TRANSPARENCY IN CREDIT SCORING ACT

Rationale and Summary: For most Americans and their families, access to credit is an essential requirement for upward mobility and financial success. A favorable credit rating is invariably necessary to purchase a home or car, to start a new business, to seek higher education, and to pursue other goals. For many consumers, strong credit is also necessary to gain access to employment, rental housing, and essential services such as insurance. At present, however, individuals have very little control over how they are scored and have even less ability to contest inaccurate, biased, or unfair assessments of their credit. The credit scoring industry is now almost completely automated, with banks and lenders increasingly relying on opaque scoring tools that use numerous data sources and proprietary algorithms in order to determine which consumers get access to credit and on what terms. Traditional, automated credit scoring tools raise longstanding concerns of accuracy and unfairness. The recent advent of new "big-data" credit scoring products heightens these existing concerns of abuse, inaccuracy, and bias.

While little is known about emerging, big-data scoring tools, many claim to incorporate thousands of data points into their models, including such factors as a consumer's handwriting style, social networking practices, or retail shopping habits. Alternative credit scoring may ultimately benefit some consumers, but it may also serve to obscure discriminatory, subjective, and even predatory lending policies behind a single "objective" score. There is a risk that these tools may combine facially neutral data points and treat them as proxies for immutable features such as race, thereby circumventing existing non-discrimination laws and denying credit access to certain groups. Non-transparent scoring systems may also prevent consumers from understanding what steps they should take to gain access to the economic building blocks of the American dream. While existing laws prohibit certain forms of discrimination in lending and give consumers limited rights to review and correct errors in their credit reports, these laws do not go far enough to make sure that credit scoring systems are accurate, transparent, and unbiased. Developers and users of credit assessment tools are also not required to score consumers on the basis of actual creditworthiness, raising the risk that certain products may be used to target vulnerable consumers and lure them into debt traps.

The Fairness and Transparency in Credit Scoring Act would hold developers and users of credit scoring tools to high standards of accuracy, transparency, and non-discrimination. It would prohibit credit scorers from using consumers' immutable characteristics and protected affiliations, whether directly or by proxy. The Act would also give consumers the right to understand how credit-scoring companies are evaluating their online and offline activities so that all Americans are empowered to strive for a more prosperous future. Finally, the Act would require that scores be predictive of creditworthiness, defined as a consumer's likelihood of repaying a loan and ability to do so without risking serious harm to the consumer's financial stability.

SECTION 1. DEFINITIONS. As used in this Act:

(1) "Consumer" means any individual or group of individuals, including households, family groups, and small businesses having 5 full-time equivalent employees or fewer.

(2) "Credit score" means any numerical or descriptive assessment of a consumer's creditworthiness.

(3) "Credit assessment tool" means any system, model, technique, factor, set of factors, or any other mechanism used to assess, measure, or document consumer creditworthiness.

SECTION 2. SCOPE AND APPLICABILITY. This Act applies to any entity or person (the "covered entities") that develops, uses, purchases, sells, or otherwise furnishes to a third party any credit scores or credit assessment tools if those scores and tools are used or reasonably expected to be used for any of the following purposes:

(a) To identify, target, or prescreen consumers for solicitation for credit, insurance, or financial services transactions or products;

(b) To determine whether to grant or deny any form of credit to any consumer and to set the terms under which a consumer may obtain credit;

(c) To determine whether to grant or deny any form of insurance to any consumer and to set the terms under which a consumer may access insurance;

(d) To determine whether to grant or deny any form of residential housing to any consumer, to set the terms of a consumer's residential lease, or to make any determinations regarding the extension or termination of a consumer's existing residential lease; and

(e) To determine whether to grant or deny any form of employment to any consumer, to determine conditions of employment, and to make determinations regarding employee retention and promotion;

The Act applies to any covered entity having any contacts with the State of [insert State name] on any basis that is not inconsistent with the Constitution of this State or of the United States.

SECTION 3. DISCLOSURE OF CREDIT SCORING INFORMATION.

(a) Every covered entity shall publicly disclose and disseminate, in accordance with guidelines and a standardized format to be prescribed by the Attorney General, the following information regarding the credit scores and credit assessment tools that the entity develops, uses, purchases, sells, or otherwise furnishes to a third party for any covered purpose set out in Section 2:

> (1) All classes and categories of data gathered pertaining to consumers, including, but not limited to, details of existing credit accounts, credit status and activity, salary and employment data, retail purchase data, location data, and social media data;

> (2) The types of sources from which each data category is obtained and the collection methods used to gather such data, including the collection methods used by any third party data vendors; and

> (3) A complete list of all individual data points and combinations of data points that a credit score or credit assessment tool treats as significant. Each significant data point or combination of data points must be listed by order of relative importance.

(b) Every covered entity shall make and update the public disclosures described in Section 3(a) on a semiannual basis at a minimum. Every covered entity must make additional disclosures whenever there is a substantial adjustment in the categories or types data collected and used, and whenever there are any changes in the data points or combinations of data points that a credit score or credit assessment tool treats significant.

(c) Every covered entity shall make and update the public disclosures described in Section 3(a) in the following manner:

(1) By posting all disclosures on a publicly accessible, centralized source to be established by the Attorney General;

(2) By making all disclosures available to the public on the covered entity's website in a manner that is clear and conspicuous;

(3) By making a disclosure to a consumer, in a clear and conspicuous manner that is appropriate to the circumstances, whenever a covered entity uses a credit score or credit assessment tool in any of the following circumstances:

(A) When a consumer applies to receive credit, is offered or denied credit, or is solicited with an invitation to apply for credit;

(B) When consumer applies to receive insurance, is offered or denied insurance, or is solicited with an invitation to apply for insurance;

(C) When a credit score or credit assessment tool is used as a basis to offer or deny a consumer any form of rental housing, to set the terms of a consumer's residential lease, or to make any determinations regarding the extension or termination of a consumer's existing residential lease; and

(D) When a credit score or credit assessment tool is used as a basis to offer or deny a consumer any form of employment, to set the terms of the employment, or to make determinations regarding employee termination or promotion.

SECTION 4. CREDIT SCORING STANDARDS. Covered entities must ensure that credit scores and credit assessment tools meet the following requirements:

(a) They must be predictive of consumer creditworthiness, defined as the consumer's likelihood of repaying a loan or debt and the consumer's ability to do so without risking serious harm to the consumer's financial stability. To the extent that a credit score or assessment tool is designed to reflect other considerations such as lender profitability, these additional considerations must not outweigh the primary purpose of predicting consumer creditworthiness;

(b) They must not treat as significant a consumer's immutable characteristics, including, but not limited to, race, color, gender, sexual orientation, national origin, and age, unless expressly permitted under an applicable federal law. They also

must not treat as significant any data points or combinations of data points that are highly correlated to immutable characteristics, unless expressly permitted under an applicable federal law;

(c) They must not treat as significant a consumer's marital status, familial status, religious beliefs, or political affiliations. They also must not treat as significant any data points or combinations of data points that are highly correlated to marital status, familial status, religious beliefs, or political affiliations;

(d) They must employ rigorous safeguards, processes, and mechanisms to ensure that all data points are accurate, verifiable, and traceable to the specific consumer. Data must be regularly tested for accuracy, verifiability, and traceability. Data points that do not meet these requirements must not be used;

(e) They must be based on data that is derived from an empirical comparison of sample groups or the population of creditworthy and non-creditworthy consumers who applied for credit within a reasonable preceding period of time;

(f) They must be developed and validated using accepted statistical principles and methodologies; and

(g) They must be consistently revalidated in accordance with industry best practices and by the use of appropriate statistical principles and methodologies, and must be adjusted as necessary in order to maintain predictive ability as well as compliance with the standards set out in Sections 4(a) – (f).

SECTION 5. CERTIFICATION OF COMPLIANCE.

(a) Every covered entity must publicly certify that the credit scores and credit assessment tools that it develops, uses, purchases, sells, or otherwise furnishes to third parties for any of the purposes listed in the Act satisfy the standards as set out in Section 4. Public certifications of compliance shall be made on a semiannual basis, and in the following manner:

(1) By posting an affidavit of compliance on a publicly accessible, centralized source to be made available by the Attorney General. This affidavit must be signed by the covered entity's Chief Executive Officer and Chief Technology Officer;

(2) By making the affidavits of compliance available to the public on the covered entity's website in a manner that is clear and conspicuous; and

(3) By making a disclosure to a consumer, in a clear and conspicuous manner that is appropriate to the circumstances, under any of the circumstances described in Paragraphs (c)(3)(A) – (D) of Section 3 this Act.

SECTION 6. PERIODIC STATE INSPECTIONS AND AUDITS.

(a) Covered entities must retain complete, chronological records documenting changes to credit scores and credit assessment tools, including, but not limited to, the data points collected and used, the methodologies and models employed, and any other information that reasonably relates to a covered entity's compliance with the standards set out in Section 4 of this Act. Covered entities must also keep a record of all internal compliance tests and validation exercises, any material weaknesses identified, and the actions taken to address such weaknesses.

(b) The Attorney General retains the right to inspect, review, and audit a covered entity's credit scores and credit assessment tools and any documentation relating to such scores and tools in order to ensure compliance with the standards set out in Section 4. The Attorney General may employ other entities, including private auditing companies and private attorneys, to act under the Attorney General's supervision and undertake such inspections, reviews, and audits.

(c) Upon the request of the Attorney General or an entity acting under the Attorney General's supervision, a covered entity is required to furnish the following items to the Attorney General or an entity that is acting under the Attorney General's supervision, for purposes including inspection, review, and auditing to ensure compliance with this Act:

(1) All data that is collected or used for the purpose of credit scoring;

(2) The identities of all data sources and the methodologies used for data collection, including the methodologies used by any third party data vendors;

(3) Full details of the credit scoring or assessment methodology, including, but not limited to, any algorithms used, source code, and scoring guidelines and procedures;

(5) Evidence of compliance with the standards set out in Section 4, including, but not limited to, documentation of internal control and validation procedures, results of any compliance tests and validation exercises, and evidence of actions taken to address weaknesses and deficiencies in a credit scoring system.

(6) Any other information that the Attorney General or entity acting under the Attorney General's supervision deems relevant.

SECTION 7. PENALTIES. Any covered entity that fails to comply with the requirements of this Act may be liable for up to one percent of the entity's annual profits or $ 50,000 for each violation, whichever amount is greater. Any covered entity that willfully violates the requirements of this Act shall be liable for each violation for up to one percent of the entity's annual profits or $ 50,000 for each violation, whichever amount is greater. Nothing in this Act diminishes or restricts the application of other penalties that may be available under other state or federal laws.

SECTION 8. INVESTIGATIONS AND ENFORCEMENT.

(a) (1) The Attorney General shall investigate violations of this Act. If the Attorney General finds that a covered entity has violated or is violating any of its obligations under the Act, the Attorney General may bring a civil action against the covered entity.

(2) The Attorney General may employ another entity, including a private attorney, to investigate violations of the Act and to bring a civil action, subject to the Attorney General's supervision.

(b) (1) A consumer may bring a civil action for violation of Sections 3, 4, and 5 of this Act on behalf of the State of [insert State name].

(2) A complaint filed by a consumer under this Section shall be filed in [insert relevant court] in camera and ex parte, and may remain under seal for up to 60 days. No service shall be made on the defendant until after the complaint is unsealed.

(3) On the same day as the complaint is filed pursuant to paragraph (b)(2), the consumer plaintiff shall serve, by mail and electronic means, the Attorney General with a copy of the complaint, a summary of the evidence compiled by the plaintiff, and copies of all documents that are in the plaintiff's position and that may be relevant to the plaintiff's claims.

(4) Within 60 days after receiving the complaint and disclosure of material evidence and information, the Attorney General may elect to intervene and proceed with the action.

(5) The Attorney General may, for good cause shown, move the court for extensions of the time during which the complaint remains under seal pursuant to paragraph (b)(2). The motion may be supported by affidavits or other submissions in camera.

(6) Before the expiration of the 60-day period or any extensions obtained under paragraph (b)(5), the Attorney General shall do either of the following:

>   (A) Notify the court that it intends to proceed with the action, in which case the Attorney General shall conduct the action and the seal shall be lifted; or

>   (B) Notify the court that it declines to proceed with the action, in which case the seal shall be lifted and the consumer plaintiff shall have the right to conduct the action.

 (c)(1) If, after a consumer plaintiff initiates an action and the Attorney General decides to proceed with the action, the Attorney General shall have the primary responsibility for prosecuting the action. The consumer plaintiff shall have the right to continue as a full party to the action.

(2) The Attorney General may seek to dismiss the action for good cause, notwithstanding the objections of the consumer plaintiff, if the Attorney General has notified the consumer plaintiff of the filing of the motion to dismiss and the court has provided the consumer plaintiff with an opportunity to oppose the motion and present evidence at a hearing.

(3) The Attorney General may settle the action with the defendant, notwithstanding the objections of the consumer plaintiff, if the court determines, after a hearing providing the consumer plaintiff an opportunity to present evidence, that the proposed settlement is fair, adequate, and reasonable under the circumstances.

(d)(1) If the Attorney General elects not to proceed, the consumer plaintiff shall have the same right to conduct the action as the Attorney General would have had if it had chosen to proceed. If the Attorney General so requests, the Attorney General shall be served with copies of all pleadings filed in the action and supplied with copies of all deposition transcripts.

(2) The Attorney General may, for good cause and upon timely application, intervene in the action in which it had initially declined to proceed. If the Attorney General is allowed to intervene, the consumer plaintiff shall retain principal responsibility for the action and the recovery of

the parties shall be determined as if the Attorney General had elected not to proceed.

(e) No claim for any violation of this Act may be waived or released by any covered entity, except if the action is part of a court-approved settlement of a civil action brought under this Section.

(f) For civil actions brought under this Section, the parties shall be allowed to recover as follows:

(1) If the Attorney General or entity acting under the Attorney General's supervision initiates an action pursuant to this Section, the Attorney General or the entity acting under its supervision shall receive a fixed 33 percent of the proceeds of the action or settlement of the claim.

(2) If a consumer plaintiff initiates an action pursuant to this Section and the Attorney General does not elect to proceed with the action, the consumer plaintiff shall receive an amount not less than 33 percent and not more than 50 percent of the proceeds of the action or settlement.

(3) If a consumer plaintiff initiates an action pursuant to this Section and the Attorney General elects to proceed with the action, the consumer plaintiff shall receive at least 15 percent but not more than 33 percent of the proceeds of the action or settlement of the claim, depending upon the extent to which the consumer plaintiff substantially contributed to the prosecution of the action. The Attorney General shall receive a fixed 33 percent of the proceeds of the action or settlement of the claim.

(4) All remaining proceeds shall go to the Treasury of the State of [insert State name].

(5) If the Attorney General, an entity acting under the Attorney General's supervision, or a consumer plaintiff prevails in or settles any action under this Section, the entity acting under the Attorney General's supervision or the consumer plaintiff shall also receive an amount for reasonable expenses that the court finds to have been reasonably incurred, plus reasonable costs, including experts fees, and attorney's fees. All expenses, costs, and fees shall be awarded against the defendant and under no circumstances shall they be the responsibility of the State.

(f) If a consumer plaintiff initiates or proceeds with an action under this section, the court may award the defendant reasonable expenses, costs, and attorney's fees only if the defendant prevails in the action and the court finds that the

claim was frivolous, vexatious, or brought primarily for purposes of harassment.

(g) Once the Attorney General, an entity acting under the Attorney General's supervision, or a consumer plaintiff brings an action under this Section, no other person may bring a related action under this Act based on the facts underlying the pending action.

SECTION 9. RELATIONSHIP WITH EXISTING LAWS. Nothing in this Act expands, diminishes, impairs, or otherwise affects the rights and obligations of covered entities under the Fair Credit Reporting Act, the Equal Credit Opportunity Act, or any other applicable federal laws. Nothing in Section 8 of this Act limits or restricts the right of persons to bring actions under other state and federal laws, even if these actions are based on the same or similar facts as an action brought under Section 8 of this Act.

SECTION 10. SEVERABILITY. If any provision of this Act or its application to any person or circumstance is held invalid, the invalidity does not affect other provisions or applications of this Act that can be given effect without the invalid provision or application, and to this end the provisions of this Act are severable.

<u>ANNEX 2</u>: THE MODEL FATSCA SECTION-BY-SECTION

Section 1. Definitions
- **Consumer:** Refers to any individual person or group of persons including households, family groups, and small businesses with fewer than five full-time employees. This definition ensures that the Act applies regardless of whether the covered entity is dealing with an individual, a group of persons, or a small family-owned business.
- **Credit Score:** A numerical or descriptive assessment of a consumer's creditworthiness.
- **Credit Assessment Tool:** a system, model, technique, factor, set of factors, report, or any other mechanism used to score assess consumer creditworthiness. This definition encompasses traditional credit scores as well as emerging "big data" tools.

Section 2. Scope and Applicability
- Section 2 defines "covered entities" based upon whether they develop, use, purchase, or sell credit scores or credit assessment tools for specific, defined purposes. The category of "covered entities" is broad enough to encompass lenders that use credit scores and assessment tools, even when the tools are entirely developed by third party vendors.
- The category of covered entities does not encompass all entities that might also be deemed "credit reporting agencies" (CRAs) under the Fair Credit Reporting Act (FCRA). For example, companies that merely assemble consumer data might be deemed CRAs under the FCRA, but they would not fall within the Act's scope of application unless they also evaluate that data as part of a credit scoring or assessment exercise.
- The Act's scope is further limited to certain specific contexts or purposes. A covered entity will fall under the Act's requirements when the score or assessment tool is used or should be expected to be used for any of the following purposes: 1) to identify, target, or prescreen consumers for credit products, financial products, or insurance products; 2) to grant or deny credit to any applicant and to set the terms of access to credit; 3) to grant or deny insurance to any applicant and to set the terms of access to an insurance product; 4) to grant or deny residential housing to any consumer; and 5) to grant or deny employment to any applicant or make decisions regarding employee promotion and retention.

- The Act applies to the fullest extent permitted by both the state and Federal Constitution.

Section 3. Disclosure of Credit Scoring Information

- This section establishes transparency minima for the types of information that covered entities must make publically available regarding their scores and tools. They must publish information regarding the categories of data collected, the sources and techniques used to acquire that data, and the specific data points that a tool uses for scoring.
- While covered entities do not need to disclose every individual data point that they collect, they must provide a particularized description of the data points or combinations of data points that their models deem significant. For example, if an assessment tool treated the number of "likes" that a Facebook user receives per week as a significant factor, the entity would be required to describe this data point with particularity, and could not merely rely on a more generic description such as "social media activity."
- If a tool treats a combination of data points as significant when combined, the combination must be described, even though each data point may not be individually significant. Covered entities must also rank significant data points (or combinations thereof) by order of importance. This will better enable regulators and the public to ascertain whether a credit score or assessment tool is indirectly considering prohibited characteristics such as race.
- The Act does not define the term "significant" in reference to data points or combinations of data points. Significance must be determined on a case-by-case basis for each model or assessment tool given that a change in the particular type of model used may affect whether a data point is significant, even if all other factors are held constant.
- Covered entities must report the above information in three ways: 1) by disclosure on a publically accessible website established by the Attorney General; 2) by public disclosure on the entity's own website; and, 3) through disclosures to consumers when a score or assessment tool is used in credit, insurance, rental housing, or employment transactions.

Section 4. Credit Scoring Standards

- The Act sets out minimum standards for all credit scores and assessment tools,. Several have been adapted

from the Equal Credit Opportunity Act's (ECOA) Regulation B, which requires all automated credit scoring tools that consider age as a factor to be "empirically derived, demonstrably and statistically sound." *See* 12 C.F.R. 202.2(p).

- Credit scores and assessment tools must be predictive of creditworthiness, meaning a consumer's likelihood of repaying a loan and ability to do so without risking serious harm to the consumer's financial stability. This standard is meant to ensure that lenders will not employ credit assessment tools target vulnerable consumers, or to prioritize lender profit over a consumer's financial stability. Scoring and assessment tools may consider other objectives as long as consumer creditworthiness remains the central focus.

- Credit scores and assessment tools must not treat as significant, either directly or indirectly, immutable characteristics such as race. This standard seeks to prevent covered entities from using facially-neutral data points as proxies for sensitive characteristics.

- Credit scores and assessment tools also must not take into account, either directly or indirectly, a consumer's marital or familial status, or religious or political affiliations.

- If a data point or combination of data points is strongly correlated to any immutable characteristics or protected affiliations, it cannot be used. A data point can be used, however, if it is only weakly correlated to a prohibited characteristic or affiliation.

- Credit scores and assessment systems must be backed by rigorous safeguards and mechanisms to ensure that the raw data are accurate, verifiable, and traceable to the consumer. For example, covered entities must ensure that they have mechanisms in place to prevent data from consumers with similar names or social security numbers from being combined. Covered entities are obligated to verify the underlying data they collect and use, and to have robust systems in place to identify and eliminate errors.

- Credit scores and assessment tools must be developed and validated using accepted statistical principles and methodologies, as currently required under ECOA's Regulation B. This requirement can be met if a score or assessment tool is based on an accepted modeling technique such as a regression analysis or a decision tree analysis. They must also be based on data that are derived from an appropriate sample.

- Finally, scores and assessment tools must be continuously revalidated to ensure that they remain predictive, and that they remain in compliance with the Act's other standards.

Section 5. Certification of Compliance
- Covered entities must publically report and certify that their credit scores and assessment tools meet the standards established in Section 4. They must make this self-certification of compliance through an affidavit and in the same manner as described in Section 3.. Certifications must be made or updated twice per year.
- In addition to encouraging compliance, the self-certification may permit state and federal regulatory agencies such as the FTC to pursue actions against non-complying entities.

Section 6. Periodic State Inspections and Audits
- This Section authorizes the state attorney general, or a private auditing firm or attorney acting under the attorney general's supervision, to inspect or audit a covered entity at any time to test for compliance with the standards set out in Section 4. The attorney general will be given *in camera* access to all elements of a scoring or assessment system, including algorithms, source code, and repositories of data.
- Any consumer data made available to the attorney general will not be used for purposes other than inspection or audit. It cannot be used in an investigation or proceeding against a consumer, or furnished to any other law enforcement or regulatory body for such a purpose.

Section 7. Penalties
- The Act gives a court discretionary ability to impose a penalty of up to $50,000 or one percent of the covered entity's annual profits, whichever is greater, for each instance in which a covered entity violates the Act's requirements. For each willful violation, the Act imposes a mandatory penalty of $50,000 or one percent of the covered entity's annual profits, whichever is greater.

Section 8. Investigation and Enforcement
- The Act gives the state attorney general, or another entity acting under the attorney general's supervision, primary enforcement authority. If the attorney general does not act, a consumer may bring suit on the state's

behalf. A consumer plaintiff does not need to prove any form of damage in order to have standing in the suit.

- If a consumer plaintiff initiates a suit, the attorney general will have the opportunity to intervene and either proceed with the action or seek dismissal for good cause. If, after a consumer plaintiff has initiated a suit, the attorney general intervenes and decides to proceed with the action, the consumer plaintiff can continue to participate as a full party. If the attorney general initially decides not to intervene, it may do so at a later point if the consumer plaintiff is not adequately representing the state's interests.
- The Act sets out a formula by which the attorney general, its designate, and any consumer plaintiff can share in any civil penalties awarded. The Act also allows private plaintiffs to recover reasonable expenses, costs, and attorney's fees for successful actions or settlements. In cases where a court deems the consumer plaintiff's suit to be frivolous or vexatious, the court may also award expenses, costs, and fees to the defendant entity.

Section 9. Relationship with Existing Laws
- The Act does not expand, diminish, or impair covered entity's rights and obligations under the FCRA, the ECOA, or any other applicable federal law.

Section 10. Severability
- Any provisions of the Act that are invalidated, for example if they are preempted by federal law, can be severed from the Act without affecting the Act's remaining provisions.