

February 7, 2020

## Memorandum

**To:** Members, Committee on Financial Services

**From:** FSC Majority Staff

**Subject:** February 12, 2020, “Equitable Algorithms: Examining Ways to Reduce AI Bias in Financial Services”

---

The Task Force on Artificial Intelligence of the House Financial Services Committee will hold a hearing entitled, “Equitable Algorithms: Examining Ways to Reduce AI Bias in Financial Services,” on February 12, 2020 at 2:00 p.m. in Room 2128 of the Rayburn House Office Building. This single-panel hearing will have the following witnesses:

- **Dr. Philip Thomas**, Assistant Professor and co-director of the Autonomous Learning Lab, College of Information and Computer Sciences, University of Massachusetts Amherst
- **Dr. Makada Henry-Nickie**, David M. Rubenstein Fellow, Governance Studies, Race, Prosperity, and Inclusion Initiative, Brookings Institute
- **Dr. Michael Kearns**, Professor and National Center Chair, Department of Computer and Information Science at the University of Pennsylvania
- **Ms. Bärí A. Williams**, Attorney and Emerging Tech AI & Privacy Advisor
- **Mr. Rayid Ghani**, Distinguished Career Professor, Machine Learning Department and Heinz College of Information Systems and Public Policy, Carnegie Mellon University

### Overview

There is no single, commonly agreed upon definition of Artificial Intelligence (“AI”) broadly or within financial services.<sup>1</sup> The term AI is often conflated with the technological capabilities and desired outcomes AI systems pursue. As *Figure 1* below illustrates, AI is a broad field involving systems representing intelligent behavior across a range of cerebral tasks (e.g., alphabetically organizing all people with income under \$50,000). And one of the key technologies in AI is machine learning (“ML”).<sup>2</sup> ML is best defined as a process that may rely on pre-set rules to solve problems (also known as algorithms) without or limited human intervention (e.g., fraudulent transactions tend to have these features or how to price an illiquid security).<sup>3</sup> The aforementioned techniques can also find patterns in large amounts of data (e.g., concluding that consumers who often search for payday loan providers once a month compared to consumers who search two times a month are likely to be paid monthly).

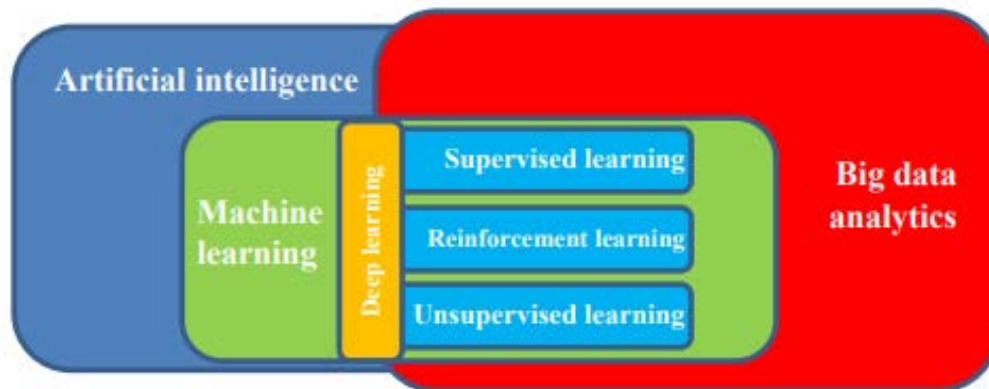
---

<sup>1</sup> Artificial Intelligence Task Force on of the House Financial Services Committee, “Perspectives on Artificial Intelligence: Where We Are and the Next Frontier in Financial Services,” Jun 26, 2019 at <https://financialservices.house.gov/calendar/eventsingle.aspx?EventID=403824>.

<sup>2</sup> Financial Stability Board (“FSB”), “Artificial intelligence and machine learning in financial services,” Nov. 1, 2017 at <https://www.fsb.org/wp-content/uploads/P011117.pdf>.

<sup>3</sup> *Id.*

**Figure 1: An Overview of AI, Machine Learning, and Big Data Analytics<sup>4</sup>**



Many observers assert that both industry and regulators would benefit from setting standards and developing tools to ensure that AI technology is reliable, accurate, and fair.<sup>5</sup> The National Institute of Standards and Technology’s (“NIST”) has published a document entitled, “U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools,”<sup>6</sup> and the Office of Management and Budget (“OMB”) and Office of Science and Technology Policy (“OSTP”) have jointly released, “Principles for the Stewardship of AI Applications.”<sup>7</sup> NIST’s plan identifies nine focus areas for standards, including data and knowledge, performance testing and reporting methodology, risk management, and trustworthiness. The NIST plan recommends tools to support the advance of reliable and trustworthy AI programs. OMB’s and OSTP’s guidance include ten principles focused on using pilot programs, deferring to independent standards organizations, and directing that new AI regulations should limit regulatory oversight.<sup>8</sup>

### **Ethical and Big Data Concerns in AI**

The concerns and risks of algorithmic decision-making and AI technologies are well documented.<sup>9</sup> Generally, the complexity of decision-making processes utilized in these technologies makes it difficult for human programmers to predict what the program will do and explain why it did what it did.<sup>10</sup> The complexity problem stems from opaque and ever evolving algorithms, especially those dealing with large

<sup>4</sup> See FSB, *supra* at 2.

<sup>5</sup> Laura Kayali, Politico, “Alphabet, Google CEO: Artificial intelligence needs to be regulated,” Jan.20, 2020, at <https://www.politico.eu/article/alphabet-google-ceo-artificial-intelligence-needs-to-be-regulated/>.

<sup>6</sup> National Institute of Standards and Technology, “U.S. Leadership in AI: A Plan for Federal Engagement in Developing Technical Standards and Related Tools,” Aug. 9, 2019, pg. 3-6, at [https://www.nist.gov/system/files/documents/2019/08/10/ai\\_standards\\_fedengagement\\_plan\\_9aug2019.pdf](https://www.nist.gov/system/files/documents/2019/08/10/ai_standards_fedengagement_plan_9aug2019.pdf).

<sup>7</sup> Russel T. Vought, “Memorandum to the Heads of Executive Departments and Agencies, “Guidance for Regulation of Artificial Intelligence Applications,” Jan. 13, 2020, at <https://www.whitehouse.gov/wp-content/uploads/2020/01/Draft-OMB-Memo-on-Regulation-of-AI-1-7-19.pdf>; See also, the White House, “Artificial Intelligence for the American People,” (last accessed Feb. 6, 2020) at <https://www.whitehouse.gov/ai/>.

<sup>8</sup> *Id.*

<sup>9</sup> See for example, David Stein, “AI in Lending: Key Challenges and Practical Considerations,” Law 360, August 9, 2018, at <https://www.law360.com/articles/1071151/ai-in-lending-key-challenges-and-practical-considerations>; Robert Bartlet, Adair Morse, Richard Stanton, et al., Consumer Lending Discrimination in the Era of Fintech, University of California-Berkley working paper, October 2018, at <https://faculty.haas.berkeley.edu/morse/research/papers/discrim.pdf>.

<sup>10</sup> Also known as the “black box” problem which means (1) models are too complicated for any human to understand or (2) models are proprietary. Cynthia Rudin, “Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead,” National Machine Intelligence, pg. 206–215, May 13, 2019, at <https://doi.org/10.1038/s42256-019-0048-x>.

data sets.<sup>11</sup> Regardless of how financial institutions underwrite a loan or extend credit, utilizing an unexplainable algorithm raises significant concerns in light of the need to comply with existing laws and regulations.<sup>12</sup> Further, human programmers may unknowingly write historical biases into their programs. The potential for programmers to perpetuate historical bias unintentionally may be exacerbated if the companies and teams developing the programs lack racial and ethnic diversity, as well as diversity of experiences and points of view.<sup>13</sup>

In addition to the technical concerns of algorithmic decision-making and AI technologies, it is equally important to focus on the data sets that are being used by AI. The data sets can contain errors, are incomplete, and/or contain data that reflect societal or historical inequities.<sup>14</sup> Substandard data or “dirty data” is problematic for AI programs because, all following inferences are susceptible to inaccuracies, incompleteness, or non-representative information.<sup>15</sup> A financial services illustration of “dirty data” is exemplified by the under-representation of protected groups (e.g. sex, race, color, national origin, etc.) in historical loan data. Because members of these groups have been less likely to be approved for loans, historical loan data sets are made up of non-representative samples of the population. In this instance, if the historical data is input into a ML program determining the likelihood to pay back, the program would likely learn and rank those from groups historically unaffected by bias and discrimination higher because of more available data to analyze.<sup>16</sup>

### **Enforcing Existing Laws and Frameworks**

Congress has enacted several laws to combat historic racism and discrimination, including: (1) the Equal Credit Opportunity Act (“ECOA”) which, generally prohibits discrimination in credit transactions based upon certain protected classes;<sup>17</sup> (2) the Fair Housing Act which prohibits discrimination and provides fair access to housing and other housing-related services;<sup>18</sup> and, (3) the Fair Credit Reporting Act (“FCRA”), which requires consumer reporting agencies to adopt reasonable procedures that are fair and equitable with regard to the confidentiality, accuracy, relevancy, and proper utilization of consumer data.<sup>19</sup>

Applying the existing legal framework where rights and protections are clearly defined to these AI technologies could pose challenges for regulators as they attempt to gauge compliance with many of these laws that do not contemplate the use of AI.<sup>20</sup> In addition, the institutions using the algorithm must be able to explain to regulators: (1) why something happened, (2) why something else did not happen, (3) how

<sup>11</sup> FINRA, “Know Before You Share: Be Mindful of Data Aggregation Risks,” Mar. 29, 2018, at <https://www.finra.org/investors/alerts/be-mindful-data-aggregation-risks>, *see generally*, Penny Crosman “Is Finra's dire warning about data aggregators on target?” Apr. 9, 2018, at <https://www.americanbanker.com/news/is-finras-dire-warning-about-data-aggregators-on-target>.

<sup>12</sup> Penny Crosman, “Can AI’s ‘black box’ problem be solved?” American Banker, Jan. 1, 2019.

<sup>13</sup> Nicol Turner Lee, Paul Resnick, and Genie Barton, “Algorithmic bias detection and mitigation: Best practices and policies to reduce consumer harms,” Brookings Institute, May 9, 2019, <https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/>.

<sup>14</sup> Thomas C. Redman, “If Your Data Is Bad, Your Machine Learning Tools Are Useless,” Harvard Business Review, Apr. 2, 2018, at <https://hbr.org/2018/04/if-your-data-is-bad-your-machine-learning-tools-are-useless/>.

<sup>15</sup> *See* Redman, *supra* at 12.

<sup>16</sup> *See* Lee, Resnick, and Barton, *supra* at 13.

<sup>17</sup> 15 U.S.C. §§1691-1691f. Historically, ECOA has been interpreted to prohibit both intentional discrimination and disparate impact discrimination, in which a facially neutral business decision has a discriminatory effect on a protected class. However, the Supreme Court’s reasoning in a June 2015 decision involving the Fair Housing Act, has sparked debate about whether disparate impact claims are covered under ECOA.

<sup>18</sup> 42 U.S.C. §3601, §3605.

<sup>19</sup> 15 U.S.C. §1681.

<sup>20</sup> McKinsey Global Institute, “Notes from the AI frontier: Tackling bias in AI (and in humans),” Jun. 2019, at <https://www.mckinsey.com/~media/McKinsey/Featured%20Insights/Artificial%20Intelligence/Tackling%20bias%20in%20artificial%20intelligence%20and%20in%20humans/MGI-Tackling-bias-in-AI-June-2019.ashx>.

failure and success are defined, and (4) how are errors corrected.<sup>21</sup> Presently, these factors translate into regular audits of algorithms for bias and discrimination by regulators or independent third-parties.<sup>22</sup> A similar system is in place in the Europe Union, where its General Data Protection Regulation (“GDPR”) requires organizations to be able to explain their algorithmic decisions.<sup>23</sup>

Some observers argue that companies deploying algorithmic decision-making and AI technologies need “regulatory sandboxes,” that provide certainty that they will not face enforcement for non-compliance of regulations for a certain period if they meet certain conditions designed to limit consumer harm and ensure additional monitoring.<sup>24</sup> However, stakeholders have raised concerns about sandboxes because a company could be immune from enforcement actions by any federal or state authorities, as well as from lawsuits brought by private parties.<sup>25</sup> Another example, is the Consumer Financial Protection Bureau’s (“CFPB”) No Action Letter policy, best exemplified by Upstart (an alternative data lending company).<sup>26</sup> In 2017, Upstart received a No Action Letter from the CFPB with regard to whether its underwriting models complied with certain fair lending rules and laws.<sup>27</sup> The No Action Letter also required Upstart to routinely test its underwriting model for performance and share those results with the CFPB.<sup>28</sup> However, a recent report has found that the company may be engaged in education redlining.<sup>29</sup> Further, the Trump administration recently proposed changes to the Department of Housing and Urban Development’s disparate impact standard under the Fair Housing Act,<sup>30</sup> which includes safe harbors that would make challenging algorithmic bias incredibly difficult.<sup>31</sup>

---

<sup>21</sup> Matt Turek, “Explainable Artificial Intelligence,” DARPA, at <https://www.darpa.mil/program/explainable-artificial-intelligence>.

<sup>22</sup> See Lee, Resnick, and Baton, *supra* at 11.

<sup>23</sup> James Guszczka, Ilyad Rahwan, Will Bible et al., “Why We Need to Audit Algorithms,” Harvard Business Review, November 28, 2018, at <https://hbr.org/2018/11/why-we-need-to-audit-algorithms>.

<sup>24</sup> See for example, State of Arizona, House of Representatives, 53rd Legislature, Second Regular Session 2018, House Bill 2434, at <https://www.azleg.gov/legtext/53leg/2R/bills/HB2434H.pdf>; State of Wyoming, House of Representatives, 65th Legislature, 2019 General Session, Enrolled Act 34, at <https://www.wyoleg.gov/2019/Enroll/HB0057.pdf>.

<sup>25</sup> National Consumer Law Center, “Consumer Bureau’s Shocking New “No Consumer Protection” Policy,” Dec. 11, 2018, at <https://www.nclc.org/media-center/pr-consumer-bureau-s-shocking-new-no-consumer-protection-policy.html>.

<sup>26</sup> CFPB, “CFPB Announces First No-Action Letter to Upstart Network,” Sep .14, 2017, at <https://www.consumerfinance.gov/about-us/newsroom/cfpb-announces-first-no-action-letter-upstart-network>.

<sup>27</sup> *Id* at 12-14.

<sup>28</sup> *Id*.

<sup>29</sup> Student Borrower Protection Center, “New Report Finds ‘Educational Redlining’ Penalizes Borrowers Who Attended Community Colleges and Minority-Serving Institutions, Perpetuates Systemic Disparities,” Feb. 5, 2020, <https://protectborrowers.org/new-report-finds-educational-redlining-penalizes-borrowers-who-attended-community-colleges-and-minority-serving-institutions-perpetuates-systemic-disparities/>

<sup>30</sup> The disparate impact standard holds actors accountable for the discriminatory impacts of their actions regardless of whether the discrimination was intentional. House Financial Services Committee, “FSC Disparate Impact Letter to HUD,” Nov. 22, 2019, at [https://financialservices.house.gov/uploadedfiles/fsc\\_disparate\\_impact\\_letter\\_to\\_hud\\_-\\_11.22.19.pdf](https://financialservices.house.gov/uploadedfiles/fsc_disparate_impact_letter_to_hud_-_11.22.19.pdf); see also, American Bankers Association, Consumer Bankers Association, and the Housing Policy Council, “Joint ABA, CBA, HPC Comments on HUD’s Proposed Rule on Fair Housing Act Disparate Impact,” Oct. 18, 2019, at <https://www.aba.com/advocacy/policy-analysis/joint-comments-to-hud-re-disparate-impact> and The Business Software Alliance, “HUD’s Consideration of the Fair Housing Act’s Disparate Impact Standard Docket No. FR-611-P-02; RIN 2529-AA98,” at <https://www.bsa.org/files/policy-filings/10182019rehuddisparateimpact.pdf>.

<sup>31</sup> House Financial Services Committee, “Committee Majority Slams Carson’s Proposal to Gut the Fair Housing Act,” Nov. 22, 2019, at <https://financialservices.house.gov/news/documentsingle.aspx?DocumentID=404847>