Response Document

Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, including Machine Learning

Prepared for

Agencies:

Board of Governors of the Federal Reserve System,

Bureau of Consumer Financial Protection,

Federal Deposit Insurance Corporation,

National Credit Union Administration,

and Office of the Comptroller of the Currency.

Prepared by Tiger Analytics

July 1, 2021

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I. Cover Page

OFFICE OF THE COMPTROLLER OF THE CURRENCY
Chief Counsel's Office Attention: Comment Processing
Office of the Comptroller of the Currency 400 7th Street SW, Suite 3E—218 Washington, DC 20219
[Docket ID OCC—2020-0049]

BOARD OF GOVERNORS OF THE FEDERAL RESERVE SYSTEM
Ann E. Misback, Secretary,
Board of Governors of the Federal Reserve System
20th Street and Constitution Avenue NW
Washington, DC 20551
[Docket No. OP-1743]

FEDERAL DEPOSIT INSURANCE CORPORATION
James P. Sheesley
Assistant Executive Secretary
Attention: Comments-RIN 3064-ZA24 Federal Deposit Insurance Corporation
550 17th Street NW
Washington, DC 20429
[RIN 3064- ZA24]

BUREAU OF CONSUMER FINANCIAL PROTECTION
Comment Intake,
Bureau of Consumer Financial Protection
1700 G Street NW
Washington, DC 20552.
[Docket No. CFPB-2021-0004]

NATIONAL CREDIT UNION ADMINISTRATION
Melane Conyers Ausbrooks
Secretary of the Board,
National Credit Union Administration
1775 Duke Street
Alexandria, VA 22314-3428
[Docket No. NCUA-2021-0023]

Re: Request for Information and Comment on Financial Institutions' Use of Artificial Intelligence, Including Machine Learning (RFI)

Dear Agencies,

Tiger Analytics (Tiger) welcomes the opportunity to submit its views and response for the request for information (RFI) and comment on financial institutions' use of artificial intelligence (AI), including machine learning (ML), by the Board of Governors of the Federal Reserve System (FRB), Bureau of Consumer Financial Protection (CFPB), Federal Deposit Insurance Corporation (FDIC), National Credit Union Administration (NCUA), and Office of the Comptroller of the Currency (OCC).

Tiger Analytics (www.tigeranalytics.com) is a global analytics firm specializing in creating bespoke AI and ML based solution to help their clients generate business value through data and analytics. At Tiger, we solve complex business problems that develop from an idea and is then brough to life via proof-of-value (POV), reusable artifacts and the culture of Open Innovation. This is spirit of how we deliver value to our clients and our teams. This is how we get the job done.

With the proliferation of AI and ML in almost all part of decision making at Financial Institutions (FIs), this step by the Agencies is very timely and very commendable. The easy availability of tools, technology, and talent will further help the FIs to lead the innovation not only for the financial services industry but also set an example for other industries. As such, we welcome this joint effort by the Agencies to solicit comments and initiate a discussion on the use AI and ML models. This joint discussions between agencies also facilitates bringing together a diverse set of views. We are eager to see the outcome of this exercise result in agreement and uniformity of definitions, separation of facts from myth, and gradation of actual and perceived risks arising from the use of AI and ML models.

Some discussion for AI and ML techniques may become too academic. In general, we have refrained from deep technical discussions and presented our thoughts in a generic language as far as possible.

Ultimately the role of regulations around newer techniques such as AI and ML is to create fairness and transparency for everyone. This is completely in line with what we believe and offer by developing and deploying powerful AI and ML solutions for our clients, whether large or community bank, credit unions, fintech, and other financial services.

Thank you for your consideration.

Badrish

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II. Explainability

Question 1: How do financial institutions identify and manage risks relating to AI explainability? What barriers or challenges for explainability exist for developing, adopting, and managing AI?

Question 2: How do financial institutions use post-hoc methods to assist in evaluating conceptual soundness? How common are these methods? Are there limitations of these methods (whether to explain an AI approach's overall operation or to explain a specific prediction or categorization)? If so, please provide details on such limitations.

Question 3: For which uses of AI is lack of explainability more of a challenge? Please describe those challenges in detail. How do financial institutions account for and manage the varied challenges and risks posed by different uses?

Risk identification and management related to AI explainability is a continuous process that needs to sit across AI/ML model development lifecycle. The methods and processes have evolved significantly over years with development of frameworks such as Feature importance, Partial dependence plots, LIME, SHAP, EL5, surrogate models for complex ML explainability and frameworks like Integrated Gradients for deep learning.

However, given a lack of industry wide consensus and standardized framework for interpretation and explainability is one of the major causes of lack of trust in AI algorithms. The term 'explainability' and a closely associated term 'interpretability' themselves are so new that a common definition needs to be established. The traditional statistical way of explaining and interpreting the results in simpler language does not work for ML models. Doing so tantamount to force fitting an esoteric idea into very simple language, and that itself may increase the risk while giving a false sense of security to the FIs and the regulators.

For example, "*We deny you a credit because of your recent delinquency*" is an easy explanation understood by all. This had worked well within the bounds of traditional modeling methods. With ML techniques, the explanation may as well be, "*We would have denied you credit because of your recent delinquency, but we noticed that the reason you missed your payment might be due to huge bill on your car repair a few months ago. That could have been an unforeseen situation. You have been generally on time with your rent and utility payment and it appears you are responsible with your expenses. Hence we approve your credit application and are giving you a favorable term.*" Finding such complex interactions and features help banks take more calculated risks and ultimately help in ease of access to credit and banking services for the underserved.

In the current maturity, use of AI is a challenge where there are fair lending regulations governing credit approval, a potential of a disparate treatment exists, and the impact on a customer is either direct or indirect i.e., models that recommend products, voice recognition engines that detect fraud during a telephonic conversation, etc. Some black box vendor solutions continue to pose the challenge on explainability. Although ML solution providers have started to provide reasons or reason codes for further analysis, verification, etc.

Even though FIs have started to leverage advanced ML explainability metrics, it still needs some workaround and business user education, standardization and simplification to ensure wide-scale adoption and effective implementation. Creating and deploying an ML-based decision requires stakeholders across departments to collaborate. With recent development in end-to-end tools that allows embedding DevOps principles within the AI model development life cycle, the focus of defining ML explainability is becoming a continuous process rather than a one-time post-development activity.

Recent publication by National Institute of Standards and Technology (NIST) on the Psychological Foundations of Explainability and Interpretability in Artificial Intelligence[1] is a welcome development as it will bring more consensus from an independent organization like NIST.

It should be noted that FIs are already evaluated on strong risk and control practices and such governance process is also applicable for AI models. FIs with established safety and soundness programs can use the time-tested structures for traditional modelling, that is, model governance, independent model validation, and model monitoring, to manage risks related to AI models and its features too.

III. Risks From Broader or More Intensive Data Processing and Usage

Question 4: How do financial institutions using AI manage risks related to data quality and data processing? How, if at all, have control processes or automated data quality routines changed to address the data quality needs of AI? How does risk management for alternative data compare to that of traditional data? Are there any barriers or challenges that data quality and data processing pose for developing, adopting, and managing AI? If so, please provide details on those barriers or challenges.

Question 5: Are there specific uses of AI for which alternative data are particularly effective?

In fact, AI and ML methods can help in managing data quality and processing optimization. There are several use cases for using advanced analytics techniques for metadata management, data traceability, fuzzy matching algorithms, automated data pipelining, and methods for data imputation which can contribute for quality and curation. Leading FIs use prevailing risk and control frameworks and audit approaches to manage these data risks.

In summary, AI can increase automation and stimulate faster decisions.

[1] See Broniatowski, David A. 2021. Psychological Foundations of Explainability and Interpretability in Artificial Intelligence. NISTIR 8367 [https://nvlpubs.nist.gov/nistpubs/ir/2021/NIST.IR.8367.pdf]

Use of proxies as an information substitute continues to pose challenges when the question of fairness and bias comes into play. Boundaries must be drawn as to where and to what degree using AI/ML tools for data quality identification and appropriate treatment is adopted. The current model risk management practices include examining sensitivity of model outcome due to data shifts. Such practices should continue for ML models too.

Bedrock of successful AI implementation is ensuring right governance, metadata management to ensure best practices across extracted, curated, labelled, and managed. Adherence to data governance standards is essential to ensure the right governance and data stewardship within the bank, however the data quality and model governance frameworks are focused on structured data. Therefore, regulations should build upon existing data governance practices for capital planning and risk management, that promulgated by supervisory guidance such as SR 15-18[2], SR 15-19[3], BCBS 239[4]. These guidance documents need to be expanded and customized for alternative and unstructured data such as text, chats, voice, video, telemetry, web personas etc. to ensure accountability, ownership and transparency. Such broad definition of data should be brought under the purview of FIs data governance program, that is usually handled by a Data Officer or equivalent.

Usage of alternative data AI has been experimented by FI's in areas of data anomaly detection (fraud, KYC, AML activities), and to provide customer a better experience. Credit reporting agencies such as Experian are using FCRA compliant and consumer permissioned data to help customer boost their credit scores[5] and thus assisting FIs expand access to their credit and banking services to otherwise underserved population. Alternative data is very relevant to explain unbanked and underbanked consumers. More importantly, these populations will have a strong benefit for their financial inclusion and access with the use of AI. Recent initiatives from CFPB's Advance Notice of Proposed Rulemaking on Consumer Access to Financial Records may provide clarity for the FIs[6]. It is also commendable to see the Agencies working together in 2019 to issue on a joint Interagency Statement on the Use of Alternative Data in Credit Underwriting[7].

Tiger Analytics, in its several analyses and projects, has found marked improvement in predictability and decision making when using alternative data for consumer, and for business. The use of alternative data has also found its use in customer servicing, making investment decision, life and non-life insurance underwriting, property and

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[2] See, SR 15-18: Federal Reserve Supervisory Assessment of Capital Planning and Positions for Firms Subject to Category I Standards [https://www.federalreserve.gov/supervisionreg/srletters/sr1518.htm]
[3] SR 15-19: Federal Reserve Supervisory Assessment of Capital Planning and Positions for Firms Subject to Category II or III Standards [https://www.federalreserve.gov/supervisionreg/srletters/sr1519.htm]
[4] See, Basel Committee on Banking Supervision. 2013 Principles for effective risk data aggregation and risk Reporting [https://www.bis.org/publ/bcbs239.pdf]
[5] See, Experian Boost™ [https://www.experian.com/consumer-products/score-boost.html, extracted July 1, 2021]
[6] See, Consumer Access to Financial Records created by CFPB. Docket CFPB-2020-0034 [https://www.regulations.gov/docket/CFPB-2020-0034]
[7] See, Interagency Statement on the Use of Alternative Data in Credit Underwriting [https://www.occ.gov/news-issuances/bulletins/2019/bulletin-2019-62.html], also on FRB, CFPB, NCUA and FDIC

casualty business, commercial real estate business and the likes. The shock from COVID-19 pandemic has created noisy signals in traditional data, this may necessitate and even accelerate the use of alternative data sources to approximate various customer, business and macro-economic parameters.

IV. Overfitting

Question 6: How do financial institutions manage AI risks relating to overfitting? What barriers or challenges, if any, does overfitting pose for developing, adopting, and managing AI? How do financial institutions develop their AI so that it will adapt to new and potentially different populations (outside of the test and training data)?

FI's have been addressing the issue overfitting as part of their traditional model development and validation lifecycle as it directly impacts model performance, lot of research has been published capturing best practices around Overfitting. FI's follow a model validation framework typically compliant with standards such as SR 11-7[8] which helps them to address overfitting for traditional models as part of the overall model risk management framework. Some of the traditional methods include looking at model performance metrics (Accuracy, GINI, KS, AUC) across Training and Test data sets.

With growing algorithmic complexity and increasing adoption of AI techniques such as ML and Deep Learning (DNNs, CNNs, KNNs), overfitting management is evolving as well. For example, traditional notion revolved around the principles of parsimony and had considered that building simple models reduces overfitting risk. However, in AI context, this needs to be relooked as in the field of deep learning the number of model input variables is not correlated with overfitting. More complex models like NNs can also help to generalize better.

Sufficient data for training AI models is one of the main challenges which leads to overfitting. For example, in computer vision problems such as image recognition availability of sufficient sample labelled is crucial for building a generalized and high performing model. However, in the real world the actual anointed and labelled datasets are limited.

This holds true for some of the traditional use-cases such as Fraud and AML. Overall, even in large FIs, the number of actual fraud cases would be limited to train the model on leading to overfitting as newer fraud scenarios would not get captured. Another challenge that FI's face is the inability to have a deeper validation for third-party models due to proprietary nature of the solution.

As algorithmic complexity (ML, Deep Learning) is increasing FI's need to assess different methodologies so that AI models are more generalized, that is, they perform well on newer populations beyond training and test datasets.

[8] See, "Guidance on Model Risk Management," Federal Reserve Supervision and Regulation Letter 11-7, https://www.federalreserve.gov/supervisionreg/srletters/srletters.htm; OCC Bulletin 2011-12, https://www.occ.gov/news-issuances/bulletins/2011/bulletin-2011-12.html; and FDIC Financial Institution Letter-22-2017, https://www.fdic.gov/news/financial-institution-letters/2017/fil17022.html.

Depending on the type of ML or deep learning technique, type of data and size of the data below approaches should be evaluated by the FIs to minimize overfitting:

- Data Integrity and sufficiency
- Data Augmentation for deep learning (Ex: Image rotation, embed noise)
- Manual feature reduction
- Cross validation such as K-fold validation
- Regularization techniques such as early stopping, L1 and L2 regularization
- Bagging, boosting and Ensembling

All things considered, the problem of overfitting is not new, it has been there since the first computation model came into existence. **The most effective counter to overfitting is an experienced model developer**, robust model development procedures, and adequate review and effective challenge by an experienced model risk personnel.

V. Cybersecurity Risk

Question 7: Have financial institutions identified particular cybersecurity risks or experienced such incidents with respect to AI? If so, what practices are financial institutions using to manage cybersecurity risks related to AI? Please describe any barriers or challenges to the use of AI associated with cybersecurity risks. Are there specific information security or cybersecurity controls that can be applied to AI?

The cybersecurity risk is indifferent from the complexity of ML models. In other words, using AI or ML methods may not increase the cybersecurity vulnerability of a financial institution with sound cybersecurity risk management practices. Conversely, not using AI or ML models, may not decrease the cybersecurity risk of the FI.

As more and more businesses move their computing and data to the cloud, we observe a symbiotic relationship develop between cloud computing and cybersecurity risk management. This is specifically true when there is a gradual erosion of the boundary between business internal data and external data. Organizations that migrate to the cloud benefit from the cost savings and thus can invest more on cybersecurity. FIs may want to put their cybersecurity focus on the data acquisition points that can even be IoT devices, and which are anecdotally the weaker links in the trust chain.

VI. Dynamic Updating

Question 8: How do financial institutions manage AI risks relating to dynamic updating? Describe any barriers or challenges that may impede the use of AI that involve dynamic updating. How do financial institutions gain an understanding of whether AI approaches producing different outputs over time based on the same inputs are operating as intended?

Traditional modelling process has a test-and-learn-and-retrain cycle. Often these cycles are long, performed offline, and the risks are adequately covered by the mode risk governance practice. With AI models, the test-and-learn-and-retrain cycle is shortened, sometimes even in near real time and are performed online. This self-learning essentially defines the 'intelligence' in artificial intelligence. **Dynamic updating is a feature, and not a bug**. Just like other aspects of model risk already described in SR 11-7, the risks associated with dynamic updating too are misspecification and misclassification of models and associated decisions. This risk is exacerbated by the high frequency of unsupervised model updates. To that effect, investing AI model monitoring process is just as important as investing in AI models.

VII. AI Use by Community Institutions

Question 9: Do community institutions face particular challenges in developing, adopting, and using AI? If so, please provide detail about such challenges. What practices are employed to address those impediments or challenges?

Tiger applauds the Agencies concern for community institutions. With the democratization of data and cloud computing, we foresee community institutions will quickly follow suit and will have access to similar technology as larger FIs. The cloud computing has lowered the hurdles by offering 'as-a-service' model for Infrastructure (IaaS), Platform (PaaS), and Analytics (AaaS). However, community institutions would have a greater reliance third party providers for tools and/or talent. Any proposed regulation and supervisory guidance should include prudent guidelines and pragmatic approached to make it easier for community institutions to access third-party solutions and services.

VIII. Oversight of Third Parties

Question 10: Please describe any particular challenges or impediments financial institutions face in using AI developed or provided by third parties and a description of how financial institutions manage the associated risks. Please provide detail on any challenges or impediments. How do those challenges or impediments vary by financial institution size and complexity?

Main challenges include black box models with poor documentation, general lack of data traceability, and difficulty to perform model maintenance.

IX. Fair Lending

Question 11: What techniques are available to facilitate or evaluate the compliance of AI-based credit determination approaches with fair lending laws or mitigate risks of non-compliance? Please explain these techniques and their objectives, limitations of those techniques, and how those techniques relate to fair lending legal requirements.

Question 12: What are the risks that AI can be biased and/or result in discrimination on prohibited bases? Are there effective ways to reduce risk of discrimination, whether during development, validation, revision, and/or use? What are some of the barriers to or limitations of those methods?

Question 13: To what extent do model risk management principles and practices aid or inhibit evaluations of AI-based credit determination approaches for compliance with fair lending laws?

Question 14: As part of their compliance management systems, financial institutions may conduct fair lending risk assessments by using models designed to evaluate fair lending risks (“fair lending risk assessment models”). What challenges, if any, do financial institutions face when applying internal model risk management principles and practices to the development, validation, or use of fair lending risk assessment models based on AI?

Question 15: The Equal Credit Opportunity Act (ECOA), which is implemented by Regulation B, requires creditors to notify an applicant of the principal reasons for taking adverse action for credit or to provide an applicant a disclosure of the right to request those reasons. What approaches can be used to identify the reasons for taking adverse action on a credit application, when AI is employed? Does Regulation B provide sufficient clarity for the statement of reasons for adverse action when AI is used? If not, please describe in detail any opportunities for clarity.

Existing Fair Lending laws and expectations needs to be overhauled to make room for innovation. Specifically, Regulation B of ECOA should be enhanced to include allowable use of ML techniques. Absent which, FIs may find it less risky to restrict their lending policy which, in turn, adversely affect marginal population. CFPB may also want to reexamine their methodology to test the disparate impact. This will provide more clarity and transparency for the lenders as well regulators to examine the fairness of the credit policies for the protected class.

X. Additional Considerations

Question 16: To the extent not already discussed, please identify any additional uses of AI by financial institutions and any risk management challenges or other factors that may impede adoption and use of AI.

Question 17: To the extent not already discussed, please identify any benefits or risks to financial institutions' customers or prospective customers from the use of AI by those financial institutions. Please provide any suggestions on how to maximize benefits or address any identified risks.

As mentioned above, AI can be very relevant to understand unbanked and underserved consumers and increase the competitiveness of FIs. Traditionally, FIs used to be the harbinger of change in the technology and algorithmic front, even for other industries. However, FIs do not have impetus to lead the innovation that makes banking services better, cheaper, and more accessible. Wider adoption of AI will have its own risks, and we believe that current regulatory structure and risk governance framework already captures most of the risks today.

We appreciate the opportunity to respond to this RFI and request the Agencies to take in recommendations and suggestions as outlined above and make appropriate clarifications and amendments.

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