THE LEGAL AND ETHICAL IMPLICATIONS OF THE USE OF ALGORITHMIC DECISION-MAKING IN CREDIT SCORING AND LOAN APPROVAL.

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ABSTRACT

The use of algorithmic credit scoring presents a wide range of opportunities and even many challenges for lenders, regulators, and even consumers.[1] *The rise in algorithmic decision-making has raised much research on fair machine learning (ML)*[2] *Financial institutions and Banks generally use ML for building scorecards that enable them and many people in the organization to decide about credits. We need to revisit the statistical fairness criteria and also examine the correctness that ML generates for credit scoring.*[3]*We need to catalog algorithmic options for incorporating goals in ML to reach the desired credit score. To compare different fairness processors for the profit-oriented credit scoring context using the real-world example.*[4] *Lending Banks have prior experience in the past of high risk for discriminatory algorithms where the use of historical data of credit scoring which have resulted in biased algorithmic tools.*[5] *In Today's world, all the data which are generated backend in the digital world are all cumulated by the social media handle and are sold to various agencies in exchange for funds. This data is then used by various Financial Institutions to base an ML for fair Credit scoring. But there are many biased in this credit scoring as this ML differs two people based on their cast, financial conditions, gender, etc which need to be changed and a*

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[1] (Remolina, 2022)
Remolina, N., 2022. *Papers.ssrn.com.* [Online]
Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4057986
[Accessed 05 May 2023].

[2] (Kozodoi, 2022)
Kozodoi, N., 2022. *sciencedirect.com.* [Online]
Available at: https://www.sciencedirect.com/science/article/abs/pii/S0377221721005385
[Accessed 05 May 2023].

[3] *Ibid*
[4] *Ibid*
[5] (Sargeant, 2022)
[Accessed 05 May 2023].
Sargeant, H., 2022. *Economic and Normative Implications of Algorithmic Credit Scoring.* s.l.:https://blogs.law.ox.ac.uk/oblb/blog-post/2022/12/economic-and-normative-implications-algorithmic-credit-scoring.

robust system of ML for credit scoring should be set up.[6] *The robust system will help the lenders to rely on the system for credit scoring which won't be biased.*

Keywords: Algorithm, Credit Scoring, Machine Learning, Artificial Intelligence

INTRODUCTION

With the explosive launch of open AI's Chat GPT, there is an emerging use of Artificial Intelligence (AI) in different areas of our day-to-day life.[7]It has played a role as the game changer in most businesses and professions and the financial sector has no exception. It has been one of the interesting areas where traditional loan sanctioning based on the credit scoring generate through the algorithm which is based on Machine Learning (ML). It has been more efficient for integrating AI and automation. But while integration has raised some serious ethical and legal concerns for the lenders where the ML lends to discrimination between the person on based various bases. [8]

DOES ALGORITHMIC LENDING MITIGATE OR PERPETUATE HUMAN BIASES??

The role of the underwriter increases as the loan portfolios are on the rise in a day come by which lends to a more complex and competitive environment that has become more challenging. For meeting the demand of this dynamic market underwriter have become more professional, more specialized, and more innovative and the use of technologies are on the rise which helps them for more accurate result and also speedy work. The creditworthiness of potential buyers is assessed more systematically and speedily. The ML also ensures that the more creditworthy buyers are approved with the loan which ensures a reduction in default and risk of financial loss to the lenders. Similarly, credit scoring is one of the technologies implemented area which this risk of default can be mitigated if proper systems are kept in place. Which will remove the human-biased sanction or credit scoring.[9]

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[6] *Ibid*

[7] (Igal, 2023)
Igal, S., 2023. *Darrow.ai.* [Online]
Available at: https://www.darrow.ai/ecoa-in-ai-driven-underwriting/
[Accessed 06 May 2023].

[8] *Ibid*

[9] *Ibid*

BUT WHAT IS THE SOLUTION WHEN THESE AI SYSTEMS THEMSELVES ARE INHERENTLY BIASED??

While reducing human bias in credit scoring and implementing AI which helps the underwriter to decide on credit decisions to reduce the risk of potential buyer's default repayment and to eliminate discriminatory lending practices, it can also lend to go in other directions that the credit is allocated on biased ways which is also not a fair way in lending funds. That is because AI works on data that is inputted in systems or which are available for them to function on a said program which is commanded in AI. The AI works on data on which they are trained, If AI is trained on biased data i.e. an algorithm that functions on biased between the person based on gender, race, religion, or says location for that matter which may be programmed or AI would have been trained in such biased data which is unfair on part of the underwriter.[10]

ALGORITHMS ARE HARNESSING A LARGE MACRO AS WELL AS MICRO-DATA THAT INFLUENCE DECISIONS THAT AFFECT PEOPLE IN A RANGE OF AREAS INCLUDING CREDITWORTHINESS

In pre algorithm period, it was humans and organizations who use to take decisions about credit lending, hiring employees for an organization, advertising for a product, sentencing a criminal, and even many more decisions they were all taken humans in charge of the said jobs, but now many of the said jobs are replaced by AI in place of humans. If the decision is not taken by a machine then the decisions taken by humans are influenced by machine or AI. [11]Algorithms are harnessing the volume of data at the micro as well as macro levels.[12] However, because machines can treat similarly-situated people and objects differently, research is starting to reveal some troubling examples in which the reality of algorithmic decision-making falls short of our expectations. Given this, some algorithms run the risk of replicating and even amplifying human biases, particularly those affecting protected groups.[13]

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[10] *Ibid*

[11] Nicol Turner Lee, P. R. a. G. B., 2019. *Brookings.edu.* [Online]
Available at: https://www.brookings.edu/research/algorithmic-bias-detection-and-mitigation-best-practices-and-policies-to-reduce-consumer-harms/
[Accessed 10 May 2023].

[12] *Ibid*

[13] *Ibid*

EXAMPLE WHERE ALGORITHMIC WERE BIASES OTHER THAN CREDIT SCORING

Biased in Online Recruitment Employee Tools

One of the largest online retail stores Amazon, whose global workforce is around 60 % male and where men hold around 74 % of the company's managerial positions has recently discounted using AI or Algorithms in recruitment after discovering that the algorithms were gender bias. The data on which such an algorithm was made was based on the last 10-year data of Amazon which generally involved males in the position and recruited in the company which was predominantly based on white males. As a result of which the female applicant for the job was unknowingly penalized due to the AI or algorithm which was used for recruitment. [14]

Biased in Online Advertisement

Latanya Sweeney, Harvard researcher, and former chief technology officer at the Federal Trade Commissioner (FTC) found that online search queries for African-American Names were more likely to return ads to such people from a service that renders arrest records, as compared to ad results for white names.[15]

Bias in Facial Recognition Technology

MIT researcher Joy Buolamwini found that the algorithms powering three commercially available facial recognition software systems have failed to recognize darker-skinned complexions. [16]

CAUSES OF BIAS

Historical Human Bias: Historical human bias is shaped pervasive and is often deeply intend to be biased which has led to AI systems being biased as the data for AI training will need to bias in algorithm too.[17]

[14] *Ibid*
[15] *Ibid*
[16] *Ibid*
[17] *Ibid*

Incomplete or Unrepresentative Training Data: The AI is not trained completely as sufficient data for training are not available for creating such an algorithm that can be complete and doesn't create bias in decision making.[18]

STRATEGIES TO DETECT BIAS

Algorithms and sensitive information: While it is intuitively appealing but the fact is that the algorithm is blind to a sensitive data field, but we cannot even set this opinion as the algorithm sometimes are blind to sensitive attributes and sometimes it considers the same. So, the strategies in detecting such bias should be to detect the data in which the algorithm is case sensitive and react to sensitive data and detect and correct the training of the AI when it is not. [19]

Detecting Bias: As discussed biases should be identifying where the algorithm is creating such biases in decision making or influencing to take such biased decision and train according to that such should not be a case in future or should be improved day by day. While detecting such bias, mostly the programmer sees the output but they should focus on the input that enters the result in bias rather than just focusing on the output which cannot help to reduce such biases.

MITIGATION PROPOSALS

Operators of algorithms must develop a bias impact statement: To mitigate such biases, we would advise operators or programmers of an algorithm to periodically prepare a bias impact report which will help them to know the progress of AI or algorithm and whether the desired result is achieved or not, they should set a target to be achieved in a particular period and should train the AI accordingly. In such a way the operator will progress and over a while, the AI will reach a level of the non-bias stage. This also helps the lending underwriter to take the decision in credit scoring and lend credibility to the creditworthiness person without being biased in the system. [20]

Which automated decisions?: In the case of determining which automated decision require operators of an algorithm should start with a question about whether the result for the question will result in negative, positive, or neutral output. Such question-to-question input or testing will help the programmer to know exactly what input or question results in biases in the

[18] *Ibid*
[19] *Ibid*
[20] *Ibid*

decision. Such an automated decision will also help the lender to know which particular data of a potential buyer when entered into the algorithm result in bias decision.[21]

What are the user incentives?: The programmer who makes the most reliable and unbiased algorithm will gain popularity and most policymakers and consumers will prefer such a programmer. Even the Potential buyer will prefer the lender who uses such an unbiased algorithm system which in turn such lender will prefer such a programmer.[22]

How are stakeholders being engaged?: A proper Algorithm lends to a proper system of a money lender and saving system which in turn results in proper working of the bank or financial institution which will lend to great return to the stakeholder or we can say directly or indirectly every stakeholder is engaging in such bias algorithm.

OTHER SELF-REGULATORY BEST PRACTICES

Operators of algorithms should regularly audit for bias[23]: The operator should always make a provision for conducting an audit of the bias regularly which will lend to the proper involvement of an external person in the system which helps to know what is the date on which the AI is trained to result in such biases?

Operators of algorithms must rely upon cross-functional work teams and expertise[24]: Many a time there are fields that the operator is not good at it so the operator should take the help of the expert in such cases, which may result in more effective work as the expert can understand the field most systemically and will help the operator to know where the training to AI by the operator is going wrong.

Increase human involvement in the design and monitoring of algorithms[25]: While designing such an algorithm the operator should make sure that the human are involved in such design on a large scale which will help the operator to know what result the algorithm reflected in case of variation of data. Human involvement also helps to know the major aspects that lead to biases in AI.

[21] *Ibid*
[22] *Ibid*
[23] *Ibid*
[24] *Ibid*
[25] *Ibid*

OTHER RECOMMENDATIONS

Consumers need better algorithmic literacy[26]: The consumers should be algorithmic literate which may help them to suggest to the lenders or underwriter to know where the credit scoring algorithm is making or influencing their decision to be biased.

CONCLUSION

So from the above discussion, we can say that at present that is an algorithm in place that lends to a biased decision in credit scoring of a potential buyer can be changed and an unbiased credit scoring algorithm can be placed with proper incorporating technical diligence, proper inspection of an algorithm by the operator or programmer, regular audit of algorithms, Regular updating of algorithm and testing on regular basis by operator till the time the system is unbiased and robust to use. Such a system in credit scoring is a must-in-need system in today's world.

[26] *Ibid*