Reviewing the socioeconomic impact of AI-based credit scoring models

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Declaration: “I declare that the work presented in this essay is my own and that it has not been submitted for assessment on any other module.”

Abstract

Credit scores[1] have been skewed towards people with better credit history since its inception, while people with little credit history may be more reliable applicants for borrowing money. This essay evaluates the alternatives to using traditional scoring models, and why they are better for global demographics. Machine learning (ML) based credit models aim to predict your future financial status through analysing your job, future employment opportunities and potential income level in the future by making use of unstructured and alternate data[2]. The main difference is that traditional scoring methods analyse your past credit history by using static formulae, while newer models predict your future credit status by identifying multidimensional patterns. While these ML-based models are ideal in theory, developers must follow a set of rules or legislation to ensure there is no bias in these models, as the underlying algorithms can become extremely entangled and complex. Applicants data must also be stored securely as these models can become a highly valuable target for hackers. These are the potential consequences to consider when switching to more accurate and inclusive credit scoring models backed by machine learning.

Credit scoring is a collection of statistical methods[3] used by financial institutions in order to judge the likelihood of a borrower to return borrowed money. In order to obtain your credit score, financial institutions will contact a Credit Reference Agency (CRA), which holds credit behaviour on its users. In the UK, the main CRAs are Equifax, Experian, and TransUnion. These agencies will look at several factors to decide an individuals score, e.g. payment history, income, types of debt, amount of debt, which are used in the credit scoring model[4]. There are many such models used, which differ agency by agency depending on the type of loan. A credit rating model based for mortgages will put a higher weighting on an individuals payment history with large loans over a long period of time, whereas a model used by credit card issuers will apply a higher weighting to consistent, smaller payments. These agencies usually represent a credit score with a numerical value ranging from 0-850, where a greater value represents increased likelihood of an individual to consistently make credit repayments. One common credit scoring model is VantageScore[5], which is used by all of the “Big Three” CRAs. VantageScore is a unique model which incorporates AI and trended credit history to allow for more accurate risk assessments. This means that users can obtain a credit score within 2 months of opening a account, as opposed to the original 6 months, because VantageScore has access to information from three credit rating agencies, which allows several million more people to get credit scores. While adopting innovative methods in credit scoring models are less biased compared to traditional statistical methods, they also come with a sense of haziness with respect to interpretation of the algorithms.

The necessity for machine-learning models stems from the issues with traditional statistical analysis methods like linear regression or discriminant analysis[6]. These sources are unbiased as they do not advocate for any model of credit scoring, just an informative piece. These methods are suitable when the underlying data points of the subjects are unbiased. This is because no statistical algorithm can intake enough data points to accurately judge an individual’s financial situation. This means that the algorithm will only take certain factors of one’s lifestyle, essentially creating an abstract version of a person, and grouping them with others that have similar factors. This means the analysis will simply output **how other people in your situation have previously behaved, not how you will behave**, which on a macro-scale seems to be accurate, since wealthier people are less likely to default on a loan. However, delving through this, we can see that this can lead to people undeservingly getting rejected, which won’t be reported as long as loans are being repaid from successful applicants. This is because of two reasons. Firstly, there is no opportunity to account for mitigating circumstances in these models, as it is fully weighted by financial statistics[7]. Secondly, there is **no feedback loop** in these models which, unlike innovative methods, disadvantages people who have been wrongly given a low credit rating. This is because all of the people that the model has given a high score tend to pay back their loans on time, but there is no feedback on those who have been given a low score. Financial institutions will generally automatically reject people that have such a low score, so there is no opportunity for the algorithm to resolve this. It is also an issue that the algorithms in traditional scoring methods are biased, which can lead to inaccurate scoring of individuals. For example, some models do not factor in utility bills, which is the main stream of credit spending for a large number of people. Therefore, by ignoring these bills, a lot of users may not have an extensive credit history which would negatively impact their credit score through no fault of theirs.

Credit scoring models based on machine learning solve a lot of the aforementioned problems with traditional scoring models. These innovative models do not put as much focus on an individuals payment history as with statistical methods, but rather focus on an **individuals future likelihood to pay back a loan**. This is done by looking at present income, employment opportunities and potential future incomes[8]. The fundamental distinction is that older models looked at an **individuals financial situation as a snapshot**, a still picture of their past, while machine learning based models treat the subject **over the future timeline**. This key difference makes credit scoring more accurate because individuals do not make payments according to their past history, but in line with their future financial situation. Machine learning allows agencies to truly assess ones "potential" to make payments on time, regardless of certain factors that heavily influence traditional scoring methods, such as length of credit history, credit bureau checks etc.

Another reason that CRAs are turning to ML based scoring models is due to the large abundance of data. Traditional methods worked well when there were limited data points (predictors) to be collected about an individual, i.e. when it was first developed in the 1950s, you could only know statistics such as amount of loans, default instances and other basic information. However in the age of Big Data[9], the amount of predictors to be collected about any single individual is far more than previously available, such as time of transaction, repayment trends etc. This abundance causes traditional linear models to be inaccurate since these models **force a structure** on set data points by applying a specific weightage and using this in a static formula. However, in ML models which use Neural Networks, unstructured data can be obtained from alternative data sources (explained below) and allow data points to have multiple weights[10] permitting the model to analyze **non-linear relationships between different factors**, which would not have been found simply by using a formula. With the increasing availability of high-power computing resources, it has become easier to train models to discover these relationships or patterns behind individual users and their likelihood of defaulting in the future, as opposed to on the basis of their past history. This model allows the scoring model to be tailored to each individual user, and replicates the accuracy level of older, judgment based credit scoring models. This is beneficial not only for individuals, but also for lenders, as they do not miss out on opportunities to make profit on safe applicants. As a result, the amount of defaults will plummet, allowing said lenders to **lower interest rates** on borrowing without impacting their margins, which in turn benefits borrowers who are deemed credit-worthy.

Another significant benefit of ML-based credit scoring models is the presence of feedback loops, which are not present in traditional statistical models. This is a feature implemented during the design of the ML model[11], which teaches the model to assess and learn from experience and allows for continuous improvement, which means that the model will be told, during the testing stage, if any applicants have been unjustly given a low score. The model will **adapt its algorithm** to account for this applicant and fixes this issue. In production, this feedback loop will allow for greater detail when giving applicants a low score by accompanying details like exactly why a score is low such as "Incrementally increasing credit without increasing income in past 3 years", as opposed to the older methods which would output “credit score is too low”. This helps credit applicants to understand what steps need to be taken in order to improve their credit, rather than a vague statement.

Such a scoring model also solves the problem of **underbanking**[12], which states that 2 billion people do not have ready access to banking solutions. This is an enormous number, and a notable reason for this is low credit scores, and how inaccurately they represent a large proportion of the world population with respect to making repayments. This is a major problem because these people are disadvantaged by not being able to make transactions, such as rent payments, since most landlords want to be paid through a bank. This will leave many people struggling to find suitable housing, and vulnerable to loan sharks or payday loans when they need to borrow money. All of these result in having a **divide** between those who have suitable access to financial services[13]. Newer machine based models like VantageScore will help to solve this issue due to the **availability of unstructured data**, and be able to process trends that emerge from the market. These models can easily adapt to market conditions, e.g. if there is onset of a recession or rising interest rates, then borrowers who had a good record of on-time payments will be allowed a certain amount of leeway on their payments before their score is affected. These models also analyse real-time transactions, such as how borrowers use credit cards, time of payments and if a borrower spends their money on luxuries or necessities. This allows the machine learning model to identify customer behaviour[14], and given that the model was appropriately trained using unbiased data sets, the model will be able to associate delinquencies **long before the user defaults** on a payment.

Furthermore, machine learning backed scoring models allow individuals with little to no credit history to get a credit score, and consequently obtain access to financial services that they would not have been able to access otherwise. Tools like Weza.io[15] use credit scoring APIs which generate a credit score using AI to collect **phone metadata** to predict credit habits of the user. This allows major institutions to accurately judge a candidate even if they do not have an extensive list of typical credit history. Similarly, data science company Tala[16] uses individuals **social media history** as a factor for credit scoring. This includes texts/calls made from the phone, app usage, merchant transactions and other personal factors which are analysed using a ML model to identify their routine habits, which is believed to be a better indicator of credit-worthiness than traditional credit scoring models. This is because the data collected can evaluate an individual well i.e. if they live within their means, if they have a strong social network, if they are detail-oriented etc. **150,000 people** have been loaned money through Tala, many of whom could not have accessed this money through traditional lenders. New financial implementations of ML-based scoring models have, to an extent, already started closing the gap between people for accessing financial services.

However, we must also look at the potential **drawbacks** of these newer ML-based credit scoring models, and their impact on the public currently, as well as when they become widely incorporated as the main method of credit scoring. The main problem with these innovative models is the **lack of transparency** involved in the complex algorithms underlying the models. This is often referred to as the **"black box"** issue with these models, since it is hard for experts to interpret and explain these algorithms[17] to ensure it is complying with regulation in place. This is a challenge because the model has a non-linear structure, with multiple dimensions, so we need to ensure that data points do not have such a relationship that breaks the law, e.g. women with kids getting a lower score because they may have to take relatively more time off from work, causing less opportunities for income growth. This is blatantly incorrect and an example of what should not be part of the algorithms underlying the models. Therefore these models need to be **thoroughly regulated** to ensure it is not showing signs of bias towards any group of people, and that it is not forming relationships which are inaccurate as this will skew the credit scores.

Another issue that may arise corresponds to **bias** in the data sets[18] before it is provided to the ML algorithms. For example, when algorithms use postcode data to judge the financial status of an individual, which may be accurate in some cases, but a lot of the data may inherently biased due to political reasons[19]. For example, certain geographical locations may be over-policed, leading to a larger number of arrests per unit area, which indicates to an algorithm that people living in that location may be less likely to repay borrowed money, which is not always true. Another example of inherent bias would be if the ML model was trained using an unsupervised method and the coressponding data set was biased[20], e.g. If there were 1000 people in a set, and 900 of those people defaulted at some time during their repayment period, if those 900 people were mostly people of colour, then this is clearly a biased set as the algorithm may create a correlation between skin color and probability of defaulting on a loan, which is clearly racism and highlights why **training sets should accurately represent the demographics**. It can be hard to verify how accurate these ML-based models are, because all data sets collected by CRAs are **proprietary**, which means that it is protected under trademark/copyright. This means that it is hard for external bodies to check how accurately the model treats the customers in the training set, and what "links" are made .This also shows why the ML space should be **strictly regulated**[21] as corporations could simply use AI as a "smokescreen" and using a blatantly unfair system such as the older judgment system to prevent lending to a certain group of people, which can lead to **severe economic and social consequences**.

Models used by Weza.io and Tala could also have extreme impact on users if not regulated correctly, as the methods used are very speculative. Using people's phone data can lead to a lot of potential users. Firstly, this model may **not accurately represent their financial capabilities**. For example, the person applying for the loan may not be the only person using the phone, and if others use the phone to idly browse for expensive luxuries, this will indicate to the algorithm that the applicant would likely live beyond their means. This in turn would lower the applicants credit score through no fault of theirs. Secondly, this model raises the question of **data security**[22], as these organisations may be the target of many hackers for the amount of valuable information they hold on several hundred thousand people. This leaves an immense amount of data vulnerable, and **legislation** must ensure that appropriate levels of security is taken to protect the data, both **online and physically**.

To conclude, traditional credit scoring models were a revolution when they originated, but with the rise of Big Data, CRAs must adapt to ML-based models which have an abundance of data points to observe patterns from, and create tailored models which are much more accurate. But this all comes with a risk[23] of inherent bias and data security, all of which must be regulated thoroughly to achieve a credit scoring system that will benefit the economic society equally.

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