Loan Algorithms and Ethics

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The practice of borrowing and lending money goes back as far as 1,800 BC in Ancient Babylon, popularized by the Greeks and Romans in the 15th and 16th centuries, and has been a cornerstone of American society since its origin.

Like most American institutions, racism and discrimination have permeated the banking industry for as long as its existence. Although one could examine this topic in-depth from various angles, the scope of this paper will focus on the advent of modern Loan Algorithms -- from the motivation and rationale for automating systems that were once performed exclusively by banks and loan officers to the consequences and problems -- intentional and unintentional.

Fair Housing Act:

In 1968, US Lawmakers passed the Fair Housing Act, which sought to eliminate discrimination perpetrated by the banking industry against marginalized communities and communities of color. Banks and other credit lenders often discriminated against these communities, denying them home and business loans in specific neighborhoods or outright. Banks and lenders provided foggy justifications to these persons seeking loans. Although discrimination was challenging to prove on a case-by-case basis, by zooming out and examining loan denials on a larger scale, lawmakers found patterns based on neighborhoods and ethnic enclaves. This practice became known as "Redlining,"; a term derived from the red line around individually denied loans in a neighborhood or area, where, once examined in aggregate on a large scale, reveals large-scale racial discrimination against communities of color.

The Fair Housing Act set specific guidelines for banks and financial institutions, explicitly protecting borrowers from discrimination based on race, color, religion, national origin, handicap, or gender.

FICO Credit Scores:

In the years following the passage of the Fair Housing Act, regulators and banking sought ways to standardize and mechanize the criteria for loan approval. Lenders used various metrics -- early algorithms -- that used specific criteria for loan approval. Although multiple methods of assessing credit existed before, modern credit scoring models began in 1958, when Bill Fair and Earl Isaac created the *Credit Application Scoring Algorithms*.

In 1989, the industry adopted the FICO credit score. The FICO credit score was adopted as a standard after Freddie Mac adopted it for all mortgage applications in 1995. The FICO credit score compiled consumer credit history and provided potential lenders with a score between 300 and 850. Financial industries pitched credit scores as an objective metric for assessing risk and granting loans.

The metrics used in the FICO Credit Score algorithm consider five components:

- Payment history (35%): Whether or not you've paid past credit accounts on time;

- Amounts owed (30%): The total amount of credit and loans you're currently using compared to your total credit limit;
- Length of credit history (15%): The length of time you've had credit;
- New credit (10%): How often do you apply for and open new accounts;
- Credit mix (10%): The variety of credit products you have, including credit cards, installment loans, finance company accounts, and mortgage loans

Algorithm implementation and unintended ethical consequences:

Removing or limiting the human element when approving or denying loan applications and putting decision-making into the hands of an algorithm is supposed to remove biases that may exist when dealing exclusively with human loan officers.

If implemented as intended, using credit scores is designed to democratize the process of applying for a loan. The premise is simple: banks use credit scores and algorithms to evaluate applicants equally based on the same financial criteria. There is no metric to consider ethnicity, neighborhoods, religion, or gender identity – all historically discriminatory fields – only the 3-digit number credit score that the algorithm devises -- technology solves a social issue.

However, the credit score algorithm and other newer and more complex loan screening algorithms do not manage to democratize the banking and lending industry. The algorithms codify the discrimination in the code itself.

For example, as of 2019, an estimated 22% or 63 million Americans are underbanked or unbanked – meaning they do not have a bank account or have limited access to financial institutions. This issue primarily affects historically marginalized communities. Persons in the most need of low-cost loans to secure housing and create businesses are the least able to receive them.

This exclusion of large swaths of the population from the modern banking industry creates various ethical dilemmas, including the advent of Pay Day loans and Guaranteed-approval loans. Both loan types are considered an "alternative" route for individuals and families who otherwise cannot borrow money based on their credit history. These loan "alternatives" have a high Annual Percentage Rate (APR) or interest and very unfavorable terms, often saddling borrowers with more debt and worsening their financial situation further. It locks borrowers into a vicious cycle perpetuated by automated banking systems, credit algorithms, and systemically biased systems.

AI Loan Approval:

Financial institutions are implementing AI systems to approve or deny loan applications to combat biases in loan approvals. These systems are fully automated and remove human input from the decision-making process. Based on a 2018 study conducted at UC Berkley, AI loan systems' objectivity is better at objectively granting loans and assessing risk; however, the quality of data that these systems are culling still preserves the historic socioeconomic biases of marginalized communities.

Researchers believe the solution to these problems is explicitly addressing biases in data – lack of credit history, credit disparity based on gender or ethnicity, increased debt, etc. – before AI computes the information. By preemptively judging the pre-existing bias before any determination is reached, based on the norming of data and providing a "fairness" layer of computing, AI loan approval has the opportunity to correct deeply historical trends in lending.

Conclusion:

Correcting hundreds of years of economic discrimination in the financial industry is challenging. Although we may look to emerging technologies to assist in the effort, no real change will occur unless the system and the deeply interconnected conditions of poverty, racism, and sexism are addressed in society first.

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