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How to fix bias concealed in credit scores

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Executive Summary

Automated credit scoring services that quantify individuals' creditworthiness are here to stay, but recent sexism accusations against some of these services have sparked concerns about algorithmic biases that could institutionalize discrimination. Credit scoring algorithms need to undergo input-through-output audits.

Algorithmic sexism?

In recent years, various companies have started offering automated credit underwriting known as credit scoring. The best-known and likely largest-scale example is Ant Financial Group's Sesame Credit. As such service has proliferated, it has drawn scrutiny for alleged sexism in a couple of cases.

Apple Card, a credit card launched in 2019 by Apple in partnership with Goldman Sachs, has been accused of being biased against women in setting credit limits. In a tweet that went viral last November, Apple cofounder Steve Wozniak revealed that his Apple Card credit limit is 10 times higher than his wife's even though they share the same Apple Card account and jointly own all of their assets.

In Japan, J.Score, a credit scoring service co-owned by Mizuho Bank and SoftBank, has likewise been accused of discriminating against women. When J.Score was tested with a pair of applications that were identical in all respects (e.g., income, profession) except gender, the woman applicant scored lower than the man. In response, J.Score has reportedly reduced gender's weighting in its scoring algorithm[1].

By utilizing a variety of data related to consumers' everyday lives in addition to their credit history and banking records, automated credit scoring can make credit ratings available to consumers who previously did not qualify for one. The scoring is done by algorithms that extract pertinent information from mountains of data and quantify it into a numerical value. At least some such algorithms are now suspected of being gender-biased.

NOTE
1) Per an April 26, 2019, Nikkei article.

Western regulatory approach to algorithmic discrimination

In Europe and the US, the potential for algorithmic (or AI-based) decisions to lead to institutionalized discrimination or bias is a serious concern. Article 22 of the EU's General Data Protection Regulation (GDPR) prohibits decision-making "based solely on automated processing, including profiling" for decisions that have legal or other significant effects on the data subject (AI-based profiling itself, however, is not prohibited). Additionally, data subjects have a right to object to automated profiling under the GDPR's Article 21[2].

2) For more information, see https://ec.europa.eu/newsroom/article29/item-detail.cfm?item_id=612053.

In the US, the Equal Credit Opportunity Act (ECOA) of 1974 bans creditors from discriminating against credit applicants on the basis of personal attributes such as gender, age, marital status, race, color, religion and nationality. The ECOA is a far-reaching law that severely restricts discrimination even in advertising and solicitations. In the Apple Card case, the New York State Department of Financial Services has launched an investigation into possible ECOA violations in response to complaints from cardholders.

Bias concealed in algorithms

In broad terms, algorithmic bias could have three causes. These causes may involve shortcomings in not the algorithm itself but the data fed into the algorithm.

The first cause is explicit use of gender or another such personal attribute as a credit scoring input. In such cases, use of the offending input must be discontinued[3].

3) However, a recent study reported that use of completely gender-differentiated credit models would raise women's credit scores. See https://medium.com/center-for-effective-global-action/gender-differentiated-credit-scores-bridging-the-gender-gap-in-access-to-credit-87e040318cdb.

The second cause is more complex. In the Apple Card case, Goldman Sachs, the card issuer, claimed that its algorithm that sets credit limits is gender-blind. However, even if an algorithm does not use gender as an input, its output may still be gender-biased if the applicant's gender can be inferred from other data. If its inputs include vocation, for example, the algorithm may be able to identify many applicants' gender with a high degree of accuracy based on whether the applicant has a job predominantly held by women (e.g., nurse, elementary school teacher) or by men (e.g., engineer, CEO). If so, credit decisions may be tinged with gender bias.

The last factor is selection bias. It occurs when a data sample under analysis is over- or under-representative of a certain subpopulation relative to the population from which the sample was drawn. The most heavily credit-scored subpopulation generally tends to comprise people confident of obtaining a high credit score. If a credit scoring algorithm is optimized based on information on people at the high-end of the credit score spectrum, it may be biased to favor members of that subpopulation.

Algorithm audits

While algorithmic automation of credit decisions as exemplified by credit scoring is an innovation that reduces lending costs and expands financial opportunity, there is a global consensus against allowing algorithms to propagate discrimination or bias. Audits of algorithms' inputs and outputs can play a key role in ensuring bias-free algorithms.

Specifically, the data used by an algorithm should be audited to confirm that they do not include any variables conducive to discrimination (and are otherwise in compliance with applicable laws and regulations). On the output side, the audit needs to confirm that credit scores are not inadvertently biased.

Such audits will require considerable statistical knowledge and expertise in business ethics. Going forward, it will be important to develop specific audit checklists in addition to training algorithm audit specialists[4].

4) For more on algorithm audits, see https://www.wired.com/story/want-to-prove-your-business-is-fair-audit-your-algorithm/.

Credit scores have the potential to become an objective credit standard untainted by human credit underwriters' subjectivity. However, we must not forget that they are formulated and used by humans.

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