Title: Optimizing Credit Limit Adjustments Under Adversarial Goals Using Causal Learning

Abstract:

Historically the decision about credit card limit adjustments has been taken primarily by expert-driven choices. In this research, we propose using data-driven techniques to solve this problem, critical not only for traditional banking but also for new business environments such as fintech companies. Our main innovation versus previous approaches is that we identify the credit limit change problem as a causal learning one, where the main goal is to estimate the individual treatment effect given a particular treatment (understood as a factor of credit limit increase) compared with being in the control group (maintain the current credit limit).

The use of these causal learning techniques presents several challenges that need to be overcome; first, the definition of the output given treatment as the expected future profit where two adversarial goals compete: maximizing the revenue brought by the customer using the card and minimizing associated account's provision. Secondly, the necessary overlap condition for comparing outcomes for treated and control groups requires creating a strategy for training propensity score models in a preliminary step, before using traditional causal models. In addition, since we aim to estimate potential outcomes that are not observable, our estimation problem is outside the umbrella of supervised learning. We use state-of-the-art methodologies for validating causal inference models in which influence functions, a technique that uses a Taylor-like expansion procedures, are employed to estimate the causal model's performance evaluation metric (known as precision of estimating heterogeneous effects) without the need to observe the true causal effects.

We use historical data from a Super-App company in Latin America to test our methodology. Preliminary results show that the causal learning models selected using the validation via influence functions can outperform the current policy for credit limit recommendations. Our research gives insights into the causal learning models' performance when deciding about increases in credit card portfolios, thus strengthening the robustness of the results over correlation-based machine leaning models, with both economics and regulatory implications.