# Data Science and the Cochabamba Water Privatization Crisis

Nisha Das

Department of Data Science

Regis University

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Prof. Ghulam Mujtaba

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**Abstract**

This report presents a comprehensive multi-week case study on fairness in credit scoring systems. The study systematically explored ethical implications, algorithmic bias, fairness metrics, and mitigation strategies in predictive modeling of credit decisions. Beginning with theoretical framing and scenario analysis, the study advanced to empirical experimentation with synthetic datasets, model training, bias detection, and mitigation through fairness-aware learning techniques. The findings emphasize the significance of transparency, interpretability, and accountability in data science, particularly when models directly affect human welfare. The final outcome offers a conclusive reflection on the responsibilities of data scientists in designing equitable systems that balance accuracy with fairness.

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## Introduction

Credit scoring has long been central to financial decision-making, influencing access to loans, mortgages, and credit cards. However, algorithmic models in credit scoring may perpetuate biases against minority groups if fairness is not addressed explicitly. This case study investigates the ethical and technical challenges of fairness in credit scoring, undertaken across multiple weeks to progressively deepen both conceptual understanding and empirical exploration. Each stage of the project integrated ethical reasoning, fairness metrics, and practical experimentation using machine learning and fairness toolkits.

## Foundational Perspectives on Fairness

We established the conceptual foundation of fairness in algorithmic decision-making. Drawing on ethical lenses, the study compared utilitarian, rights-based, and justice-oriented frameworks in evaluating credit systems. From a community-centered perspective, fairness was defined as equitable access to credit opportunities, particularly for historically marginalized groups. Ethical dilemmas highlighted in this stage included balancing financial institutions' risk management needs with social responsibilities to prevent discrimination. This stage also explored definitions of bias, distinguishing between statistical disparities and structural inequities embedded in financial data. The analysis emphasized that fairness cannot be achieved merely by optimizing accuracy; it requires embedding social values into the design of credit systems.

## Ethical Dimensions and Scenario Analysis

We advanced the discussion by examining specific scenarios of bias in credit scoring. Case-based reasoning was applied to illustrate how gender, race, and income-level disparities emerge in algorithmic models. Scenarios highlighted how different stakeholders—banks, regulators, and affected communities—frame fairness differently. Banks often emphasize profitability and compliance, while regulators focus on legality, and communities advocate for equity. The chosen stance was to adopt the role of a data scientist working on behalf of the community. This perspective demanded transparency in model assumptions, inclusivity in data representation, and accountability in communicating risks of bias. Ethical risks identified included data misrepresentation, privacy violations, and the potential for algorithmic opacity to obscure discriminatory practices.

## Model Development and Baseline Fairness Evaluation

Next, the project transitioned into empirical modeling. A synthetic dataset representing credit features such as utilization ratio, payment history, loan amount, and interest rate was generated to approximate realistic credit decision contexts. A Random Forest classifier was trained to predict binary credit approval categories. Fairness metrics such as disparate impact, statistical parity difference, and equal opportunity difference were computed across gender subgroups. The baseline results revealed disparities: approval rates were lower for females compared to males, statistical parity differences were non-zero, and equal opportunity differences highlighted unequal true positive rates. These findings underscored that even in synthetic datasets, models reflected structural inequities, validating ethical concerns raised in earlier weeks.

## Fairness Visualization and Interpretability

Then we emphasized interpretability and fairness visualization. SHAP (SHapley Additive Explanations) values were used to interpret feature contributions to model predictions, ensuring transparency in understanding which features disproportionately affected outcomes. Visualization of fairness metrics revealed gaps in approval rates and opportunity differences between subgroups. While these gaps varied in magnitude, they consistently indicated the presence of bias. From an ethical standpoint, this phase reinforced the principle that fairness analysis requires both quantitative evaluation and accessible visualization to communicate findings effectively to diverse stakeholders, including non-technical audiences.

## Fairness Mitigation Strategies and Final Evaluation

At last we focused on mitigation. Using the `fairlearn` library, fairness-aware methods such as constraint-based grid search with demographic parity were applied to retrain models under fairness constraints. Post-mitigation metrics demonstrated improvement: disparities in approval rates decreased, equal opportunity differences narrowed, and overall fairness improved, though at the expense of a slight reduction in accuracy. This trade-off reflected the central ethical dilemma in fairness-aware modeling: balancing predictive performance with social equity. The case study concluded that prioritizing fairness, even with minor sacrifices in accuracy, is ethically justified when decisions directly impact livelihoods and financial inclusion.

## Discussion

Across the seven weeks, the study revealed a consistent tension between accuracy-driven objectives and fairness-centered outcomes. While machine learning models can achieve high predictive performance, unmitigated models risk perpetuating systemic inequities. The progressive approach—moving from ethical framing to empirical modeling, interpretability, and mitigation—demonstrated that fairness is not a single-step adjustment but a continuous responsibility throughout the model lifecycle. The broader implication is that data scientists must integrate ethical reflection with technical expertise. Fairness tools provide essential metrics and methods, but human judgment is required to interpret and apply them responsibly.

## Conclusion

This multi-week case study demonstrated the intertwined nature of technical design and ethical responsibility in credit scoring systems. Beginning with conceptual discussions and concluding with fairness-aware modeling, the study underscored the importance of embedding fairness at every stage of data science practice. As credit scoring algorithms increasingly shape access to financial opportunities, ensuring fairness is not optional but essential. The final reflection affirms that data scientists hold a professional and moral duty to design systems that are not only accurate but also equitable, transparent, and aligned with social justice.