Quantifying Gender Bias in Income Prediction: A Comparative Analysis of Regression Models

Kaitlin Day, Nia Hodges, and Yuqi Yan

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Abstract

Gender disparities in income remain a pressing issue, with significant implications for social justice and economic equality [4]. This study focuses on quantifying the impact of gender on income prediction by comparing the predictive quality of popular regression models when gender data is or isn't available. Using a dataset containing demographic, educational, and occupational information, we employ regression analysis to predict income levels. Two sets of models are trained: one with gender data included and one without. The predictive performance of each model is evaluated using metrics such as mean squared error, R-squared, and bias-variance trade-off analysis. Our findings reveal the extent to which gender information influences predictive accuracy and highlight potential biases in income. By systematically comparing the performance of regression models with and without gender data, this study provides insights into the role of gender in income estimation and offers valuable implications for addressing gender disparities in the workforce. Our research contributes to the ongoing dialogue on gender equity and underscores the importance of fair and unbiased predictive modeling practices in tackling gender-based wage inequalities.

1 Project Description

The research problem addressed in this project is the quantification of gender bias in income prediction models and the assessment of how the inclusion or exclusion of gender data impacts the predictive quality of these models. This problem stems from the persistent gender disparities observed in income levels, which raise concerns about fairness, equity, and discrimination in the workforce. By employing an analytical framework that compares the performance of regression models with and without gender data, this research seeks to elucidate the extent to which gender influences income prediction and to identify potential biases in predictive modeling practices. The overarching goal is to contribute empirical evidence and insights that can inform efforts to address gender-based wage inequalities and promote gender equity in economic outcomes.

The motivation behind this work stems from the ongoing societal concern regarding gender disparities in income levels and the desire to address these inequities through evidence-based approaches. Despite advancements in gender equality efforts, significant wage gaps persist between genders across various industries and occupations. Understanding the factors contributing to these disparities, including the potential influence of gender in predictive modeling for income estimation, is crucial for designing effective interventions and policies aimed at promoting fairness and equity in the workforce. By investigating the impact of gender on predictive modeling of income, this research seeks to shed light on potential biases embedded in predictive models and their implications for gender-based wage differentials.

The research findings have the potential to impact policy decisions, organizational practices, individual decision-making, and research and development. Policymakers can use the insights to inform policies aimed at reducing gender-based wage disparities. Organizations may adjust data practices to address biases in predictive modeling. Individuals can make informed career decisions, and researchers may explore alternative modeling approaches to mitigate gender bias. The primary business/societal value of this work will be an enhancement of organizational performance by enabling more accurate and equitable decision-making processes. Economic equity and gender equality will also be positively impacted and promoted through this work. This project is important to us for a few reasons. First, we have a professional interest. We want our future work to contribute unbiased advancements to society. As women, we have a social responsibility to address gender-based wage disparities. Lastly, this project empowers individuals and organizations to advocate for gender equity and challenge discriminatory practices in predictive modeling and decision-making processes.

2 Methods

We'll train identical predictive models on datasets with and without gender information to compare their performance. If the model trained with gender data predicts income more accurately, it suggests gender's significant role. Statistical analyses will further illustrate earnings disparities across genders and industries, allowing us to quantify gender's impact on predictive modeling and highlight the gender wage gap.

We will leverage a comprehensive population survey dataset [6] sourced from the US Census Bureau website, comprising a panel study on income dynamics and a current population survey. This dataset boasts a wealth of information, including demographic details, educational backgrounds, occupational specifics, and income levels, providing a holistic view of factors influencing earnings disparities. Recognizing that not all features contribute equally to predictive accuracy, we will employ principal component analysis [3] to discern the most influential variables for model training. This strategic approach ensures that our predictive models are built upon the most salient predictors, enhancing their efficacy in capturing the complexities of the gender pay gap phenomenon.

Understanding that the quality of our analytics hinges on the quality of the underlying data, we are cognizant of the importance of robust data sources. We trust that this dataset offers the reliability and comprehensiveness necessary to yield meaningful insights. By mitigating potential data biases through rigorous analysis and validation, we aim to ensure the integrity and reliability of our predictive models, thereby enhancing their capacity to inform decision-making processes effectively. In essence, our utilization of this dataset serves as the bedrock for developing sophisticated analytics poised to elucidate the intricacies of the gender pay gap. Through a rigorous analytical approach and a commitment to data integrity, we endeavor to unveil actionable insights that propel us towards a more equitable and inclusive society.

We'll use descriptive analytics to summarize the dataset, predictive analytics to develop income prediction models with and without gender data using regression techniques, and prescriptive analytics to suggest strategies for addressing gender bias. We'll explore models like linear regression [2], random forest regression [1], and gradient boosting [5], primarily assessing performance with mean squared error (MSE) or root mean squared error (RMSE). Our goal is to provide a thorough analysis of gender bias in income prediction and offer actionable insights for promoting fairness and equity in predictive modeling.

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