Investigating Bias in Resource Allocation for Homelessness Prevention and Intervention

Abigail Santiago*
absantiago@davidson.edu
Davidson College
Davidson, North Carolina, USA

Anne Bowen*
adb@tacc.utexas.edu
University of Texas at Austin
Austin, Texas, USA

CCS CONCEPTS

• **Computing Methodologies → Machine learning approaches**.

KEYWORDS

Bias, Machine Learning, Fairness, Interpretability, Homelessness

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1 EXTENDED ABSTRACT

As technology advances at a seemingly exponential rate, many have turned to artificial intelligence and machine learning algorithms for their ability to automate decision-making processes and take mass amounts of data and gather an understanding from it, whether that be identifying patterns within the data or learning from the data to make predictions. The adoption of the use of these models and algorithms has spanned across many fields and research areas including those working to gain a better understanding of and solution to homelessness/houselessness in the United States. One problem that lends itself towards the adoption of machine learning algorithms is the problem of resource allocation. This includes the creation of predictive machine learning models that, given an individual, predicts how likely they are to become homeless, or how likely they are they to return to use homelessness services. Given these likelihoods, resources can then be allocated towards those the model deemed in the "most need."

However, even when answering a problem as important as resource allocation, there is little to no discussion on possible bias contributing to the models' decisions or the implications of using machine learning for the allocation of resources that are so scarce, as they are for homelessness. The presence of bias in these machine learning models could skew the output of the models, and therefore lead to inequities and bias when it comes to allocating the resources based on the models' decisions.

Many scholars studying homelessness, as well as the U.S. Department of Housing and Urban Development (HUD), have turned to modeling and machine learning algorithms to answer questions and solve problems surrounding homelessness. This work includes approaches such as creating predictive models for targeting interventions [2], using regression models to extract common predictors [4], and Allegheny County in Philadelphia's implementation of their Allegheny Housing Assessment, or AHA. While this work discusses the potential of machine learning models for interventions and policy making surrounding homelessness, much of their focus relies on the creation and use of the models, with the conversation on the model's overall equity not being the central focus of these approaches.

There is similar work that has been done that puts these machine learning models in conversations closely related to bias in machine learning. This work has focused on concepts such as interpretability of these models [5], as well as a discussion on the types of households the models does well for [2], and all discuss the overarching theme of the fairness of the models. However, this work differs in that the focus is on the potential bias that could affect the outputs of the model, and the concepts of interpretability and fairness are evaluated to do so, using similar methods to those found in past work.

On a high level, bias is introduced to machine learning models because they are created by humans. The data chosen for the model is chosen and labeled by humans, how the data is interacted with by the model is determined by humans, and the output is then interpreted by humans. Because of this, there are many avenues for bias in data to infiltrate machine learning models. Some examples relevant to this project are historical bias, where data reflect bias that exists in the real world; representation bias, where the way someone defines and samples a population results in bias; evaluation bias, where the evaluation of the output of the model results in bias [3]; and selection bias, where the data does not accurately represent the target population [1].

This project seeks to identify potential areas of bias in machine learning models that allocate resources for homelessness prevention and intervention by exploring the concepts of fairness and searching for signs of underspecification. Underspecification refers to the phenomenon of when a model uses many different predictors to yield the same outcome, due to the structure chosen for the given model or to selection bias within the data. This becomes an issue because it leads to unpredictable behavior during employment.

To explore fairness, A Gradient Boosted Tree Classification model was trained on the individual level data, and then its f1 scores across subgroups of race and gender were visualized to evaluate the fairness of the model. It was found that there is high variation across top features, with only one instance of common top features. The subgroups with the highest f1 scores were white men and Asian American Pacific Islander men.

*Both authors contributed equally to this research.

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To look for signs of underspecification, experiments based on the concept of Rashomon sets were conducted under several different stress tests in which a random percentage of the data used for prediction was dropped. Rashomon sets can be understood as a set of equally performing models. Two Rashomon sets were created-one containing 50 LinearSVC models, and another containing 50 Random Forest Classifier models. The f1 scores of these models were then compared. There was no difference found between the performance of the models in the Rashomon set under any stress tests. The experiments on fairness suggest bias in dataset collection. Future work suggests beginning the investigation of the found avenues of potential bias, as well performing more varied stress tests on the Rashomon set of good models.

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