



Analyzing the Interactive Effect of Race and Neighborhood Attributes in Predicting Traffic Stop Outcomes Using Artificial Intelligence

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I. Introduction

Racial bias exists in traffic stops when officers unnecessarily stop certain groups of drivers more often (Figure 1). Also, officers police some neighborhoods more due to racial composition and alcohol outlet density. This motivates us to analyze how social and built attributes interact to affect if a traffic stop results in a search and finding contraband. We use Gradient Boosting Decision Trees (GBDT) machine learning to predict the importance and interaction of factors in stop outcomes.

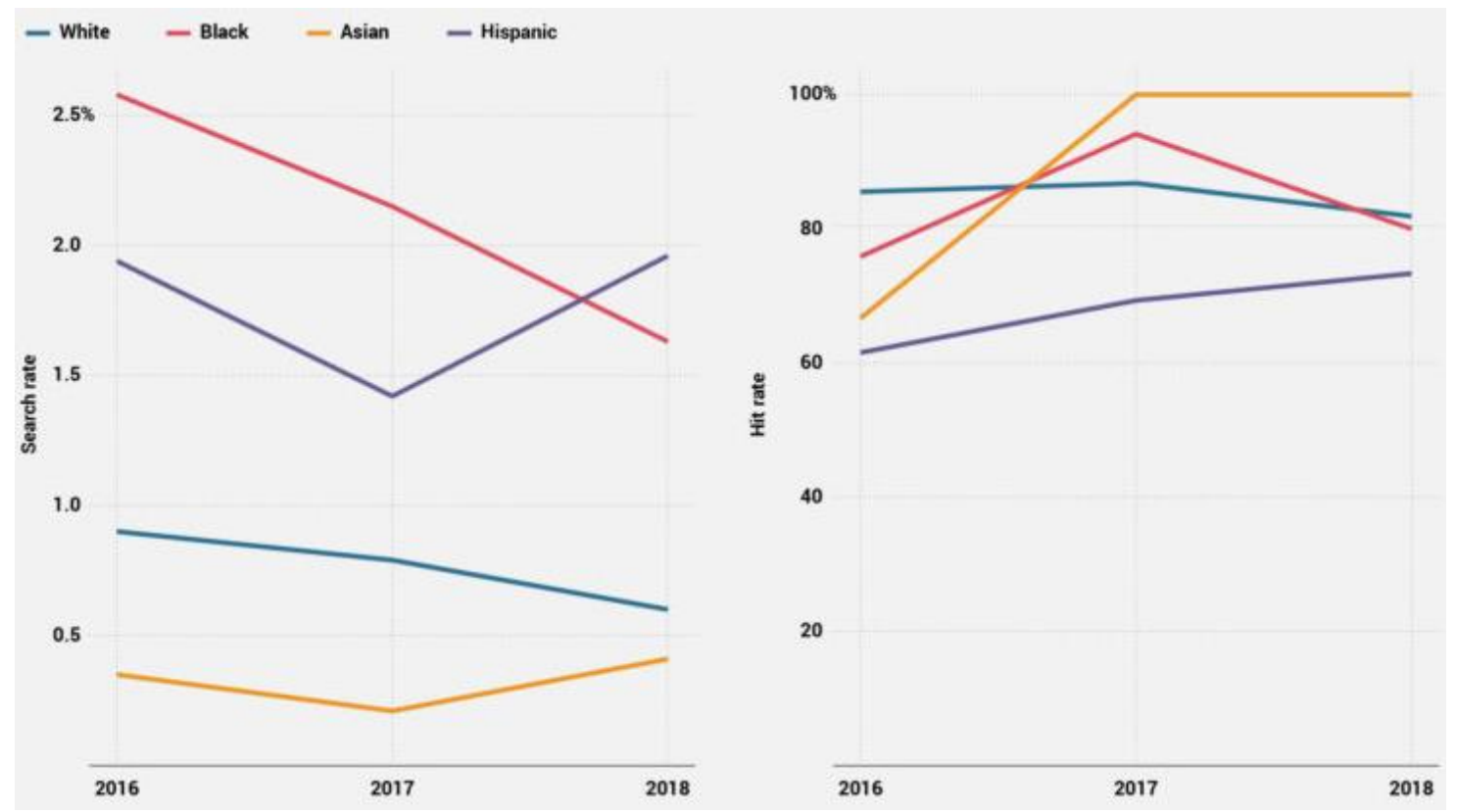


Figure 1: Traffic stop racial disparities in VT, despite contraband hit rates being similar (Norton, 2019)

II. Research Questions

- 1: What social and built attributes are related to the probability of being searched after traffic stops and the probability of discovering contraband after searches?
- 2: How can we use GBDT to quantify their interaction?

III. Dataset and Scope

Our traffic stop dataset has information for over 500,000 stops and comes from the San Diego Police Department and ArcGIS StreetMap Premium. Using the stop location information, the coordinates of the stops were matched with built and social environment data to give context on the environment where the stop took place.

IV. Literature Review

The Role of Racial Bias in Post-Stop Outcomes
Minority drivers are more likely to be searched and scrutinized more heavily, but equally likely to carry contraband (Chanin et al., 2018).

The Role of Neighborhood Characteristics in Policing
Crime varies across physical spaces, concentrating in hot spots like alcohol outlet-dense places that are heavily policed (Sherman et al., 1989; Grubestic et al., 2013). The racial composition of places of frisks can lead to racial disparities (Carroll & Gonzalez, 2014).

The Applications of the GBDT Method in Travel Behavior Studies
GBDT predicted how distance from a business district affects traffic behavior (Ding et al., 2018b).

Research Gaps
There's less literature on the interactive effect of race and built environment on stop outcomes, and regression models are less accurate than machine learning. Our project uses GBDT to add an understanding of how environment adds additional bias to decisions.

V. Methodology

The GBDT method combines multiple single decision trees to form a final prediction from multiple factors, shown below. A decision tree continually splits based on the predictor that provides the best fit.

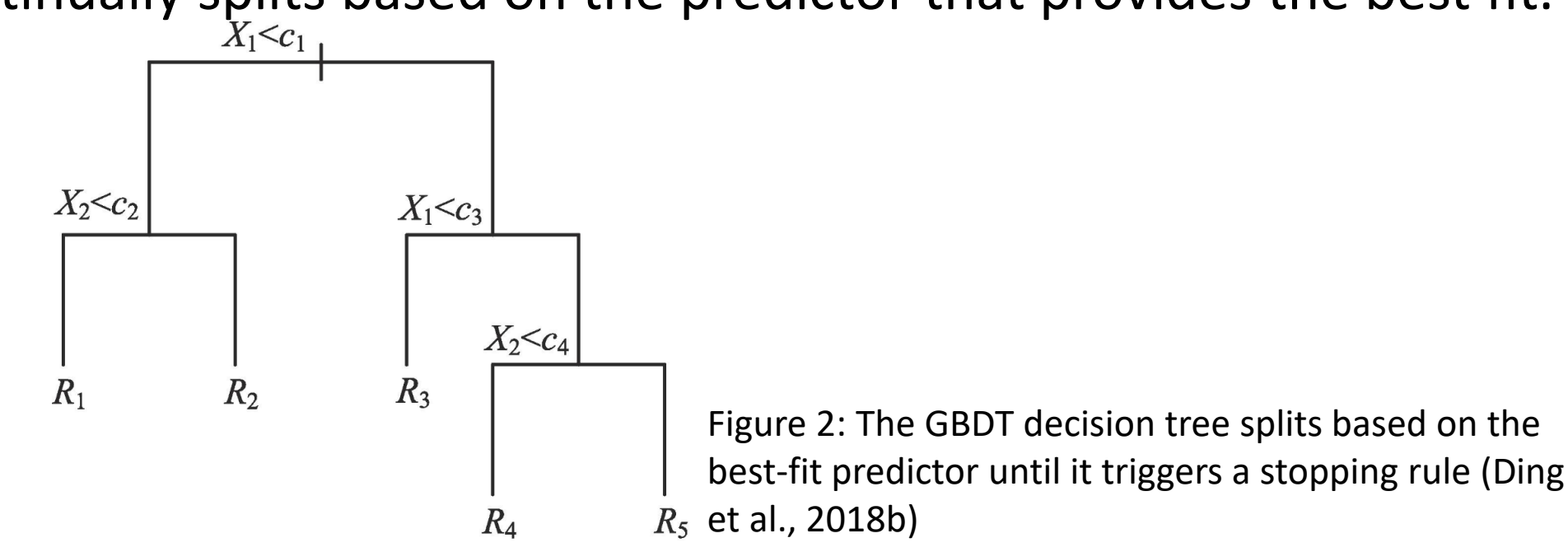


Figure 2: The GBDT decision tree splits based on the best-fit predictor until it triggers a stopping rule (Ding et al., 2018b)

We use GBDT for its precise prediction of factor importance and modeling factor interactions. GBDT can analyze if neighborhood characteristics interact with race in stop outcomes, an unexplored area in the literature.

VI. Preliminary Findings: Regression Results

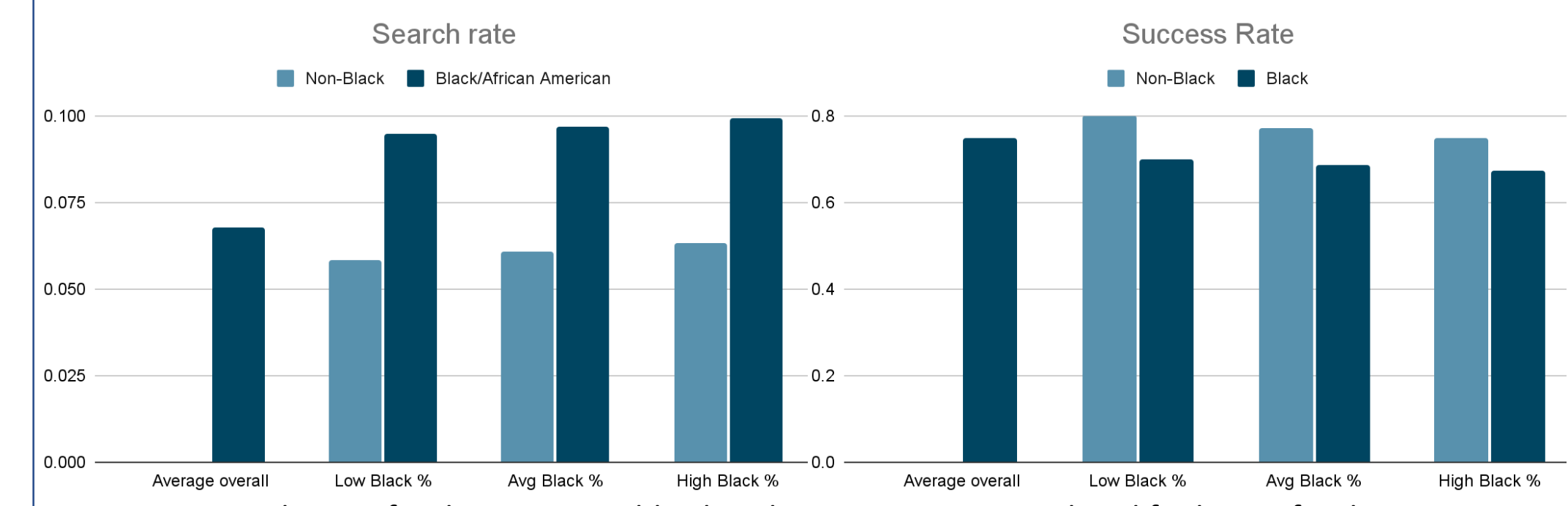


Figure 1: Search rates for drivers in neighborhoods with different Black proportions
Figure 2: Contraband find rates for drivers in neighborhoods with different Black proportions

Officers have a bias toward unsuccessfully searching Black drivers more often, and which gets worse with higher neighborhood proportions of African Americans. This suggests a relationship between racial and environmental biases impacting decisions, showing better predictive power of race and neighborhood characteristics combined.

VII. Policy Implications

Target individual factors
Reduce crime hotspots through land design for fewer stops and less policing. Reduce racial bias with implicit bias training and increased decision time (Broadfoot, 2023).

Target interactive factors
Reduce situations prone to highest bias by banning pretextual stops (Parker, 2023) and establish stricter protocol. Show that policies with extreme disparities should be abolished.

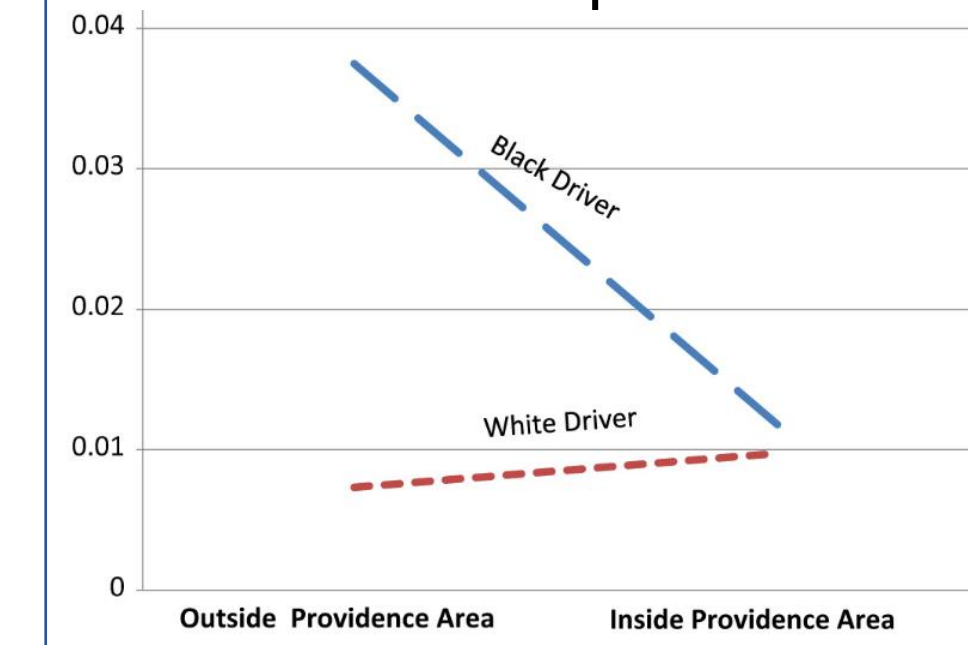


Figure 3: Frisk rates inside and outside Providence area by driver race: an example of extreme racial disparity (Carroll et al., 2014)

VIII. Next Steps

Collaborate with Dr. Tao Tao from Carnegie Mellon University, an expert in applying machine learning to transportation research. Fit models and analyze data in 2023 summer research. Attend Jan 2024 Transportation Research Board conference.

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