Predicting Charlotte Traffic Stop Outcomes Based on Driver and Officer Demographic Information

Group 3

Marianna Shaver, Jordan Register, Mitchell Jones, Srikar Vavilala, Harley Grafton

Snapshot of the Data

[Charlotte Officer Traffic Stops](#)

Charlotte Open Data Portal

Data

Officer Traffic Stops

City of Charlotte | CharlotteNC

CMPD conducts an average of 120,000 traffic stops per year. Under North Carolina state law (G.S. 143B-902-903), the CMPD as well as other law...

Type: Table
Last Updated: May 8, 2020
Rows: 139,524
Tags: Officer, Traffic, Stops

Showing 50 of 139,524 rows

Month_of_Stop	Reason_for_Stop	Officer_Race	Officer_Gender	Officer_Years_of_Service	Driver_Race	Driver_Ethnicity	Driver_Gender	Driver_Age	Was_a_Search_Conducted	Result_of_Stop	CMPD_Division
2020/01	Speeding	White	Male	27	White	Non-Hispanic	Female	38	No	Verbal Warning	University City Division
2021/05	Vehicle Equipment	Hispanic/Latino	Female	3	Black	Non-Hispanic	Male	35	No	Verbal Warning	Providence Division
2021/12	Speeding	White	Male	16	Black	Non-Hispanic	Male	29	No	Verbal Warning	University City Division
2020/01	Vehicle Equipment	White	Female	4	Black	Non-Hispanic	Male	33	No	Verbal Warning	University City Division
2020/01	Speeding	White	Male	25	Black	Non-Hispanic	Male	36	No	Citation Issued	Steele Creek Division
2020/01	Vehicle Regulatory	Hispanic/Latino	Male	3	White	Hispanic	Male	30	No	Verbal Warning	Eastway Division
2020/01	Vehicle Regulatory	White	Male	5	White	Hispanic	Male	43	No	Citation Issued	
2020/01	Vehicle Regulatory	Hispanic/Latino	Male	3	Black	Non-Hispanic	Female	27	No	Verbal Warning	Hickory Grove Division
2020/01	Vehicle Regulatory	Hispanic/Latino	Male	3	White	Non-Hispanic	Male	33	No	Verbal Warning	Westover Division
2020/01	Vehicle Regulatory	Hispanic/Latino	Male	3	Black	Non-Hispanic	Female	40	No	Verbal Warning	South Division
2020/01	Vehicle Regulatory	White	Male	3	Other/Unknown	Hispanic	Male	20	No	Citation Issued	Central Division
2020/01	Vehicle Regulatory	White	Male	8	White	Non-Hispanic	Male	32	No	Citation Issued	Westover Division
2020/01	Vehicle Regulatory	White	Male	13	Black	Non-Hispanic	Male	37	No	Citation Issued	North Tryon Division
2020/01	Stop Light/Sign	White	Male	6	Other/Unknown	Hispanic	Female	30	No	Citation Issued	Independence Division
2020/01	Vehicle Regulatory	Black/African American	Male	3	Black	Non-Hispanic	Male	36	No	Verbal Warning	
2020/01	Vehicle Equipment	White	Male	3	Black	Non-Hispanic	Male	30	No	No Action Taken	North Tryon Division
2020/01	Vehicle Equipment	White	Female	2	Black	Non-Hispanic	Female	30	No	Verbal Warning	Westover Division
2020/01	Investigation	White	Male	2	White	Hispanic	Male	22	No	Verbal Warning	Central Division
2020/01	Vehicle Regulatory	White	Male	5	Black	Non-Hispanic	Female	40	No	Citation Issued	Independence Division
2020/01	Vehicle Regulatory	White	Male	2	White	Non-Hispanic	Female	25	No	Written Warning	

Understanding the Problem

Questions we set out to answer

- **How can Machine Learning techniques be used with sociopolitical data?**
  - More specifically: are any ***protected attributes*** like ***race*** or ***gender*** significant for predicting traffic stop outcomes?
    - *This would imply potential discrimination in traffic policing.*

Note:
We realize that by analyzing this dataset, we could shed light on a potentially controversial topic.

Note that ***none of our findings should be considered causal***. Rather they shed light on ***correlations*** in the data that *may* be used to dismantle bias in policing.

Existing and Related Approaches
Novel Idea - Using ML to attack injustice

Applying machine learning methods to critique and dismantle sociopolitical injustices is an uncommon application of ML.

Prior research efforts have either:

- Focused primarily on a descriptive/statistical analysis of the data (e.g., Pierson et al., 2020).
- Did not apply ML methods (e.g., Pierson et al., 2020).
- Explored national data, requiring that they had to make subjective decisions when joining differentially labeled data across states (e.g., Pierson et al., 2020).
- Did not explore racial disparities (e.g., Hamada et al., 2018)
- Did not explore traffic stops (rather stop and frisk) (e.g., Kumar et al., 2018).

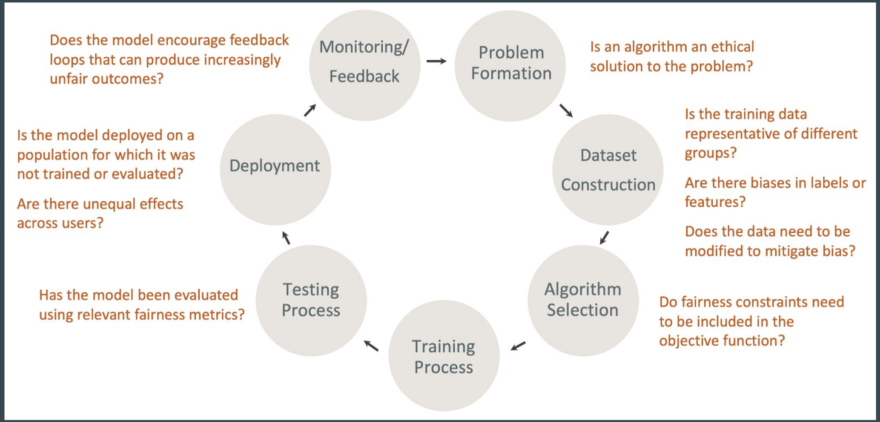
Few studies have attempted to develop a predictive model from the traffic stop data, likely due to its inherent unfairness.

Thus we set out to build **"fairness"** and **equal opportunity** into the model

Why a fair model is important

According to Hardt et al., (2016)

- ***"Despite the demand, a vetted methodology for avoiding discrimination against protected attributes in machine learning is lacking.***
- *A **naïve approach** is often used where the developed algorithm **ignores all protected attributes** such as race, color, religion, gender, disability, or family status.*
- *However, **this idea of "fairness through unawareness" is ineffective** due to the existence of **redundant encodings** (i.e. "ways of predicting protected attributes from other features") (p. 1).*

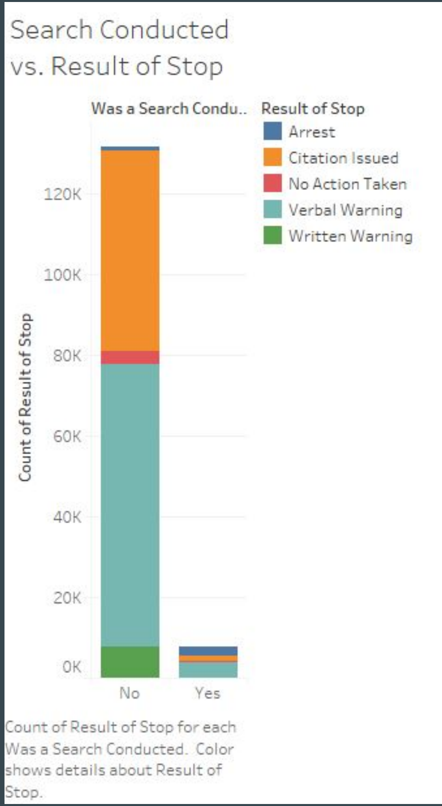


Source: [What Is Fairness and Model Explainability for Machine Learning Predictions? - Amazon SageMaker]

Exploratory Data Analysis (EDA)

[Streamlit Interactive EDA]

EDA: Reducing our target variables → RQ Modifications



A conducted search typically results in more serious consequences → Warning, Citation, Arrest.

Thus, (for feasibility) we chose "Was a Search Conducted" as our target variable.

Our research questions moving forward became:

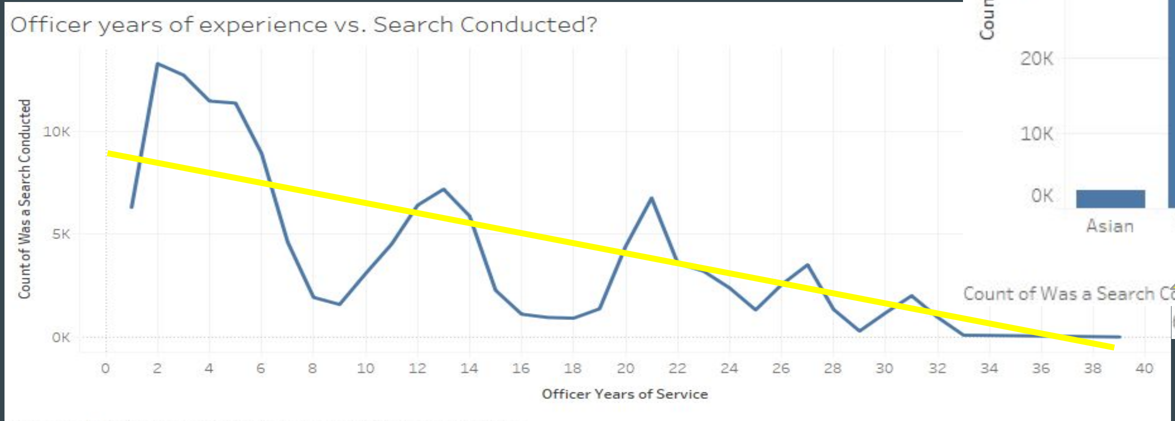
RQ#1	RQ#2	RQ#3
What ***general attributes*** correlate the most with ***whether a search was conducted.***	What ***driver attributes*** (race, ethnicity, gender, age) correlate the most with the most with ***whether a search was conducted.***	What ***officer attributes*** (race, gender, years of service) correlate the most with the most with ***whether a search was conducted.***

EDA Findings

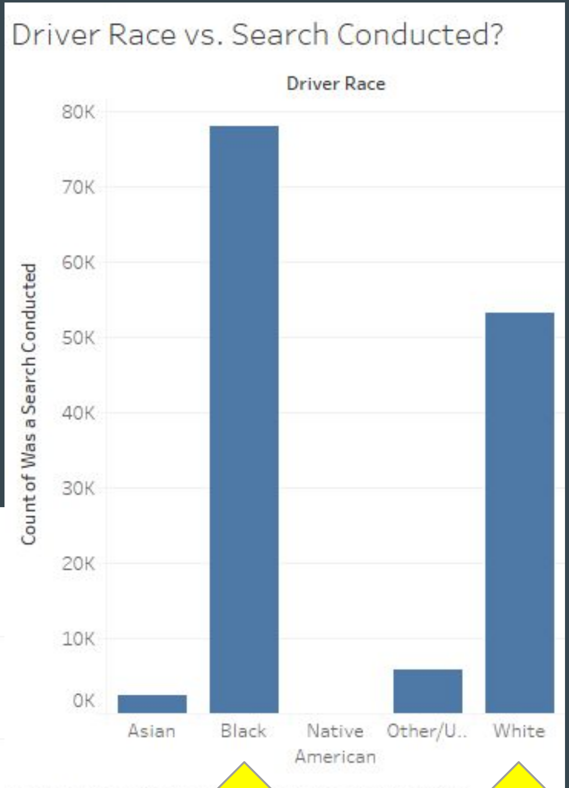
- Men are typically searched more than women
  - Men are also pulled over more than women
- Black and White people are searched more than people of other races
  - White: 49%, Black: 35% of CLT population (then why are Black people searched at a higher rate?)
- Officers with more years of experience typically search people less
  - Could be due to less officers with more years of experience being on traffic duty

Thus, we *anticipated* that:

Driver gender, **driver race**, and **officer experience** are the most significant predictors of whether a search is conducted in a CLT traffic stop.



The trend of count of Was a Search Conducted for Officer Years of Service.



Count of Was a Search Co ted for each Driver Race. G der.

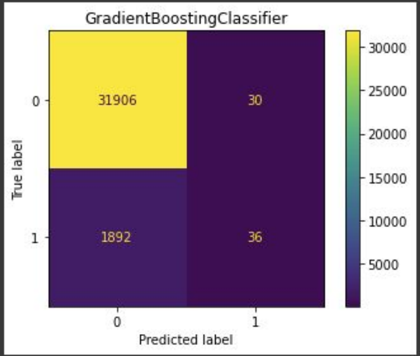
Modelling

Challenge: Upsampling is Key to Minority Class Detection

```
train['Was_a_Search_Conducted'].value_counts()
```

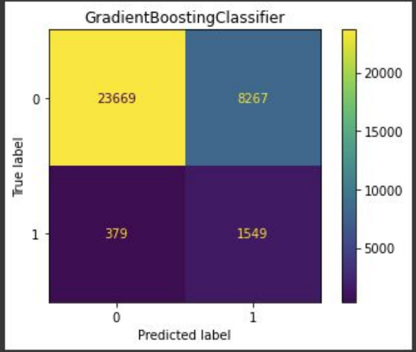
```
0    95794
1     5798
Name: Was_a_Search_Conducted, dtype: int64
```

	precision	recall	f1-score	support
0	0.94	1.00	0.97	31936
1	0.55	0.02	0.04	1928
accuracy			0.94	33864
macro avg	0.74	0.51	0.50	33864
weighted avg	0.92	0.94	0.92	33864




```
cat_cols = X.columns.isin(['Reason_for_Stop', 'Officer_Race',\
                           'Officer_Gender', 'Driver_Race',\
                           'Driver_Ethnicity','Driver_Gender',\
                           'CMPD_Division', 'Racial_Match'])
su = SMOTENC(categorical_features=cat_cols, random_state=42)
try:
  X_upsample, Y_upsample = su.fit_resample(X, Y[desired_col])
except KeyError:
  print('Could not find that column in data!')
  return _,_
print('X resample shape: {}'.format(X_upsample.shape))
print('Y resample shape: {}'.format(Y_upsample.shape))
return pd.concat([X_upsample, Y_upsample], axis = 1)
```

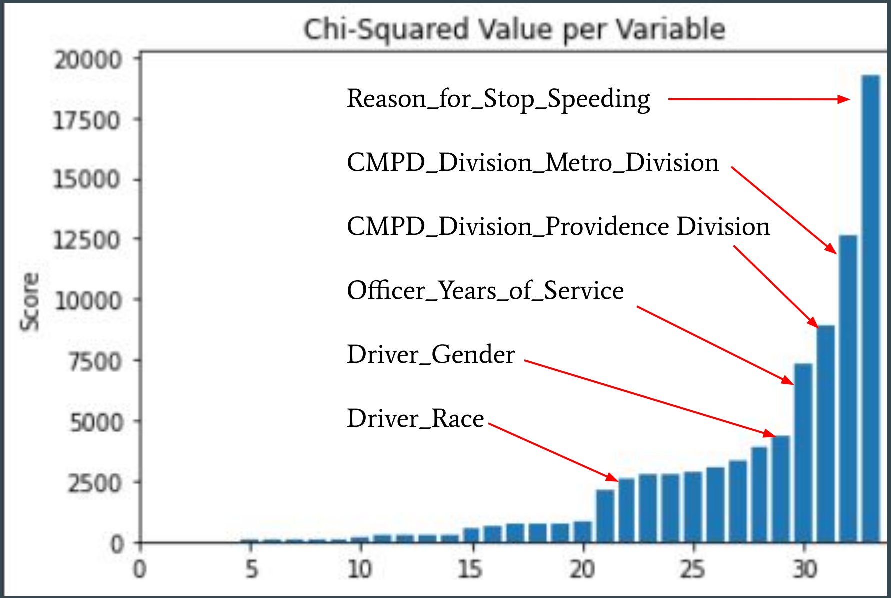
	precision	recall	f1-score	support
0	0.98	0.74	0.85	31936
1	0.16	0.80	0.26	1928
accuracy			0.74	33864
macro avg	0.57	0.77	0.55	33864
weighted avg	0.94	0.74	0.81	33864



Chi-Squared Implementation (Relevant Variables)

- The 5 most relevant features were deemed to be:
  - Reason_for_Stop_Speeding
  - CMPD_Division_Metro Division
  - CMPD_Division_Providence Division
  - Officer_Years of Service
  - Driver_Gender

- Driver_Race had the 12th highest value.



Chi-Squared Implementation Cont.

Model	Train Accuracy	Test Accuracy	Class	Precision	Recall
Gaussian Naive-Bayes	0.76	0.67	0	0.98	0.66
			1	0.13	0.81
Gradient Boosting	0.80	0.74	0	0.98	0.74
			1	0.15	0.80

Forward Feature Selection Implementation

- Interesting dropped features include:
    - Officer_Race_White
    - CMPD_Division_University City Division

- Driver_Race and Driver_Gender were deemed to be relevant.

- The metrics for the chosen models were the exact same as with the chi^2 implementation.

Is Driver Race Significant in Predictive Modelling?

Good

Race actually isn't important / isn't a huge predictor of traffic stop searches. Overall, this is a good thing, since we don't want Driver Race to be significant in predicting Traffic Stop outcome.

Bad

Makes it more difficult to form a "fair" model by comparison. However, we still found some success in this, due to Driver Race not being **completely** irrelevant in the decision making process.

Fairness and Equal Opportunity Metrics

- **P% Metric** - measures **disparate impact**. This is a measure of how the rate at which an unprivileged group receives a certain outcome compares with the rate at which a privileged group receives that same outcome.
- **Fair Classifier** - Assuming data about the predictor, target, and membership in the protected group are available, EOC attempts to optimally adjust any learned predictor so as to remove discrimination.

Definition 2.1 (Equalized odds). We say that a predictor $\widehat{Y}$ satisfies *equalized odds* with respect to protected attribute A and outcome Y, if $\widehat{Y}$ and A are independent conditional on Y.

Definition 2.2 (Equal opportunity). We say that a binary predictor $\widehat{Y}$ satisfies *equal opportunity* with respect to A and Y if $\Pr\{\widehat{Y}=1 \mid A=0, Y=1\} = \Pr\{\widehat{Y}=1 \mid A=1, Y=1\}$.

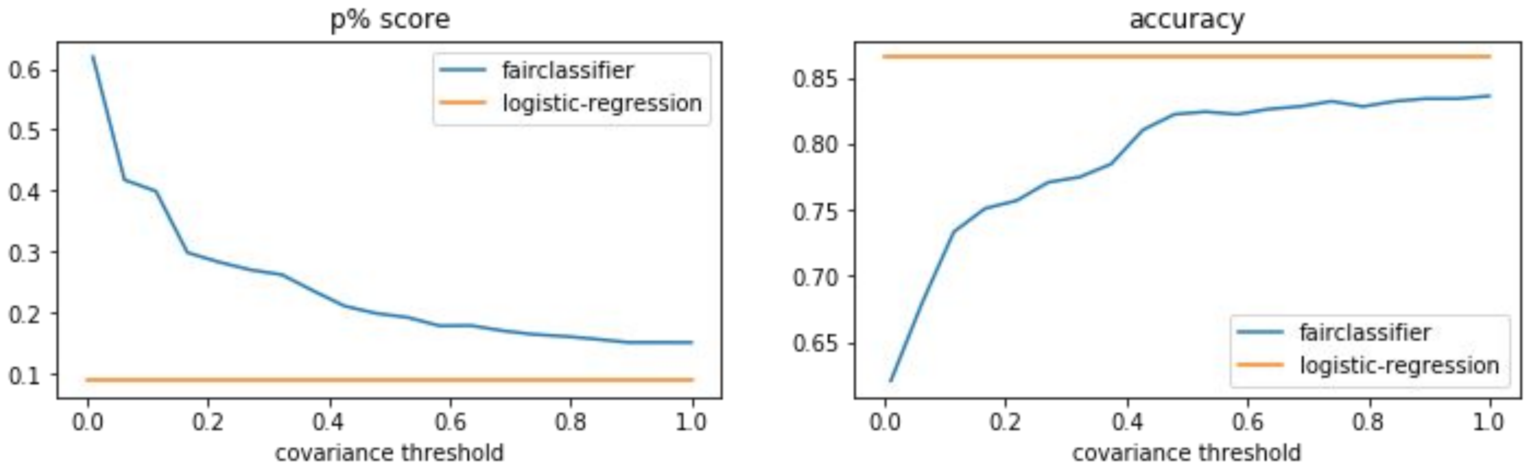
Protected attribute

Target

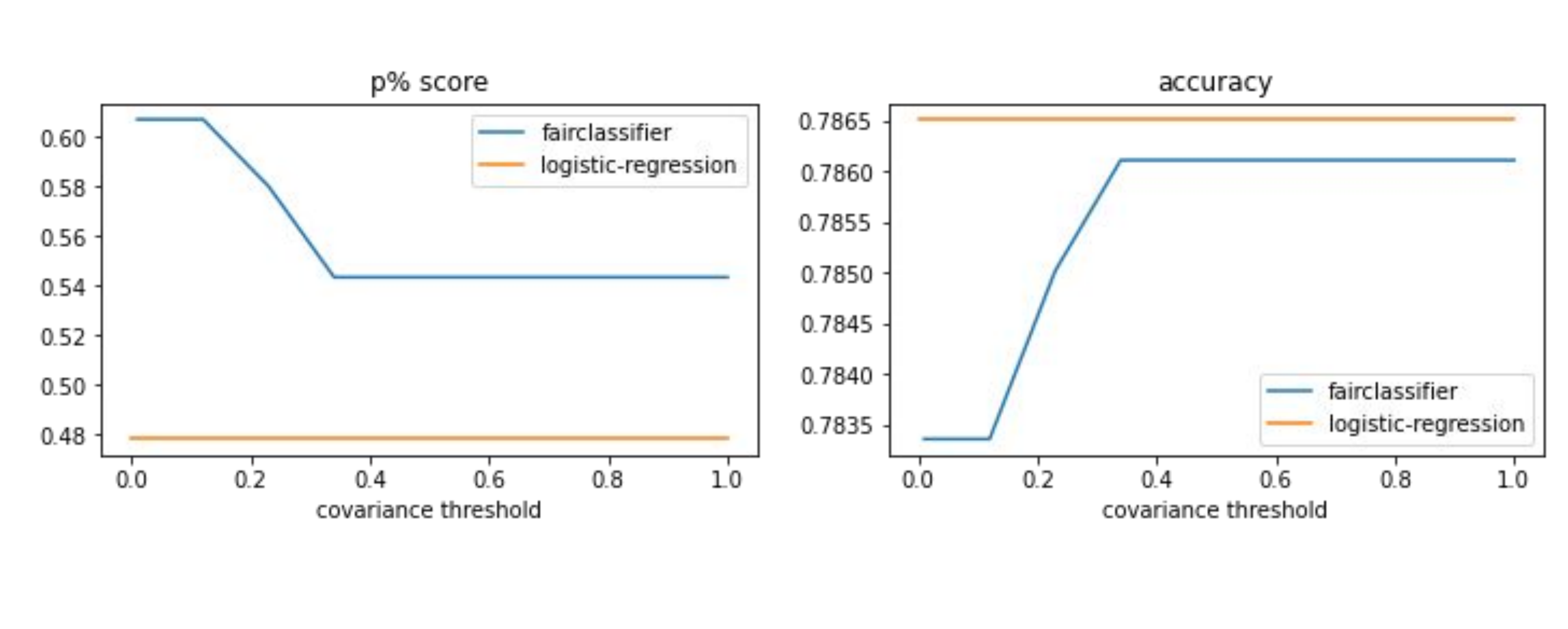
Probability of the target variable occurring without considering the protected attribute is the same as the probability of the target variable while considering the protected attribute.

Ex: Is the probability of someone being searched the same as the probability of being searched if they are Black? Female? Etc.

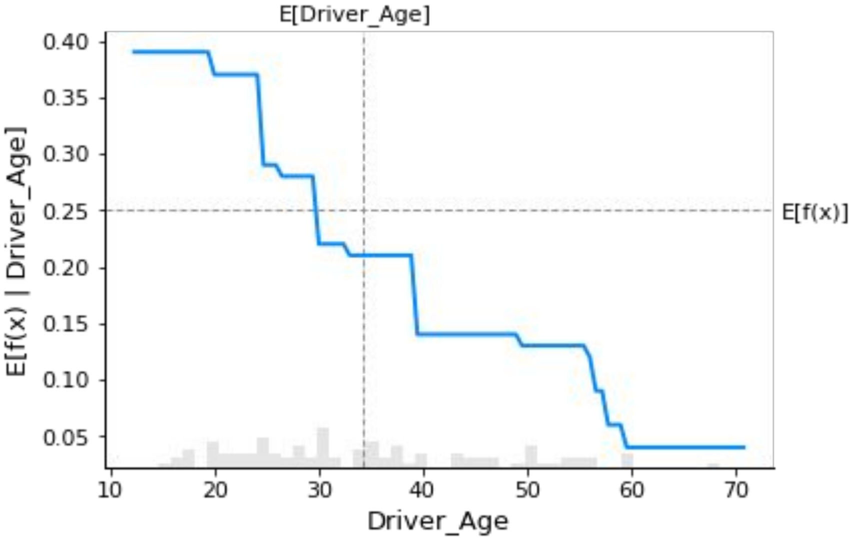
P% Tradeoff (Ideal)

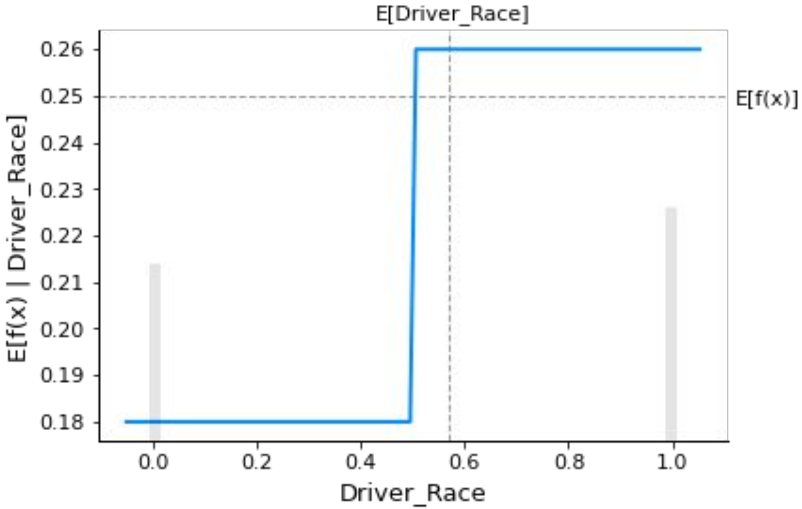


Challenge: Driver Race and P% Tradeoff



A Few Partial Dependence Plots





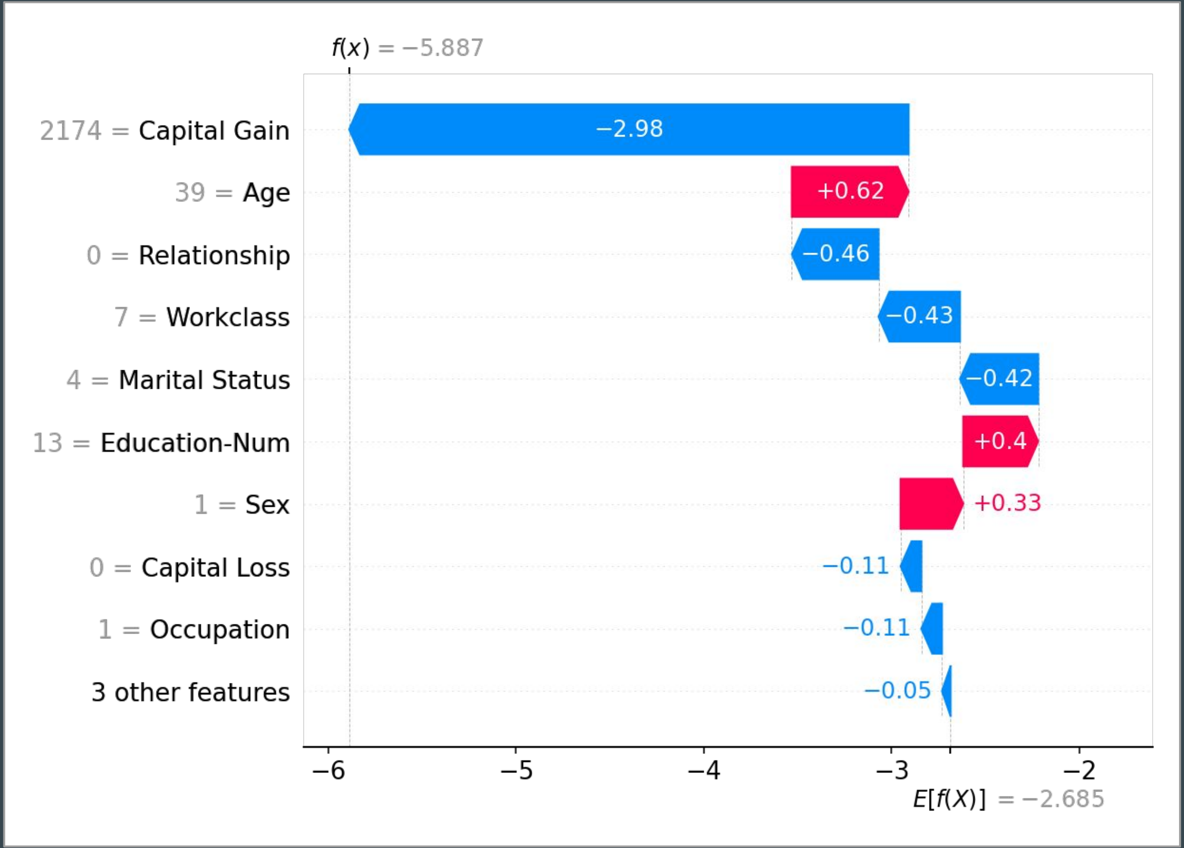
“What is Partial Dependence?”

Findings and Conclusions

Major Findings & Conclusions

Most important Predictors	Reason_for_Stop, Officer_Years of Experience, Officer Division, Driver_Gender, Driver_Race*
Effect of Fairness Metric	Very minor positive effect on model performance
Final model performance	Overall, underwhelming
Discrimination in Traffic Searches	Potentially: Black drivers are overrepresented in the dataset in every category (though Driver_Race was not a significantly predictive attribute in our modeling and analysis.)

Future Work



Future goals: Ways to include Driver Gender in a fair way, since it was more significant than Race.

The Team

Jordan Register

PhD Candidate, Mathematics Education; Data Science Grad Cert.

Srikar Vavilala

Engineer/Scientist II for the Electric Power Research Institute

Mitchell Jones

Data Analyst @ Visual Risk IQ

Harley Grafton

Business Solutions Engineer @ Charter-Spectrum

Marianna Shaver

Chemist

Data Science Grad Student