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CS109A Final Project, Group 14: Police Violence

Background & motivation

Recently, in the United States, a number of high-profile shootings of Black Americans have drawn attention to whether there are racial disparities in the use of force by the police. Due in part to these shootings, for instance, the now-prominent Black Lives Matter movement was founded in 2013 and stands against police brutality and racially-motivated violence against Black people. There have been data-driven efforts to understand whether there are racial disparities in police shootings and how this relates to department policies, but often, the data simply is lacking or nonexistent. For example, although the Department of Justice has collected and made data on law enforcement agencies available through the Bureau of Justice Statistics available since 1987, only beginning in 2015 did mainstream media companies (e.g., *The Washington Post*) start to collect and report information about fatal police shootings.

Our primary question is: do the demographics of police departments and their policies predict the race of fatal shooting victims? Using the recent data mentioned above on fatal shooting victims, combined with data on police departments, our project aims to investigate the correlates and potential causes of police violence in the United States, and make suggestions about potential mediating steps. Specifically, we test for the existence of racial disparities by predicting the race of shootings victims using information about police department policies on use of force, or combined with the demographics of the victims.

Methods

Data collection and cleaning

We sourced data from:

Source	Links	Description
The Washington Post's Police Shootings repository	https://github.com/washingtonpost/data-police-shootings	Contains fatal shootings by police officers in the line of duty in the US since 2015.
List of victims of fatal encounters with the police	mappingpoliceviolence.org	Supplements the *Washington Post* dataset with the police departments responsible for each fatal shooting and the geography of the shooting location (rural/suburban/urban).
The 2016 Law Enforcement Management and Administrative Statistics (LEMAS) dataset from the Bureau of Justice	https://www.icpsr.umich.edu/web/ICPSR/studies/37323/summary#	The most recent release of LEMAS. Contains information on the demographics and policies of police agencies.
The police use of force dataset for the largest 100 US police departments from an activist group named Campaign Zero	http://useofforceproject.org/#review	Contains information on whether each department adopts 8 core policies that restrict use of force, which we explored in EDA.
US census data	census.gov	We extracted national and county-level demographic data.

Table 1: Data sources with location and brief description.

The Washington Post's (WaPo) fatal shootings dataset and the LEMAS dataset are the primary sources for our project, and we used other datasets to supplement additional information. For WaPo, we dropped observations with NaNs. For variables on demographics and police policies in LEMAS, we imputed missing or N/A values with 0 because if an agency skips a question or answers with N/A it's more likely not to have officers of a certain race and not to have a particular policy. We used the police department information from the MappingPoliceViolence (MPV) data to bridge the merging between WaPo and LEMAS based on the unique ORI9 code for police agencies; the first police agency is taken for MPV entries with multiple police departments, and we matched the geographically nearest police department to MPV entries with unknown police department. Additionally, for LEMAS and census data, we used FIPS, a standard code for state and county, to match county-wise demographic information with police departments based in those counties.

Exploratory data analysis

To visualize the demographics of fatal shooting victims from 2015 onwards, we first examined the WaPo dataset (**Figure 1**). A majority of police violence victims were shot, with a small fraction both shot and tasered. Almost all of the victims were male and predominantly white, followed by Black, Hispanic, and a much smaller fraction were Asian, Native American, or other. Most victims did not show signs of mental illness. For threat level, a majority of the victims were perceived as attacking, although one caveat is that this metric is likely biased towards whatever the police officer reported, and thus is unlikely to say that a victim was not attacking. Most victims were not fleeing at the time of the shooting. Finally, officers were generally not wearing body cameras. When we examined the most common weapons for victims to be armed with, the top 4 were gun, knife, unarmed, and toy weapon (data not shown).

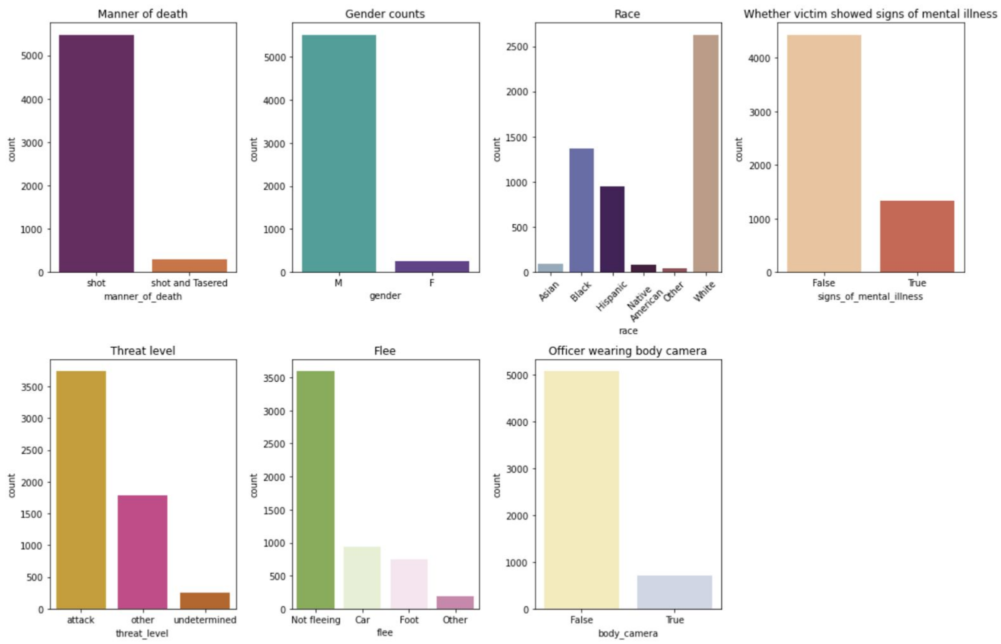
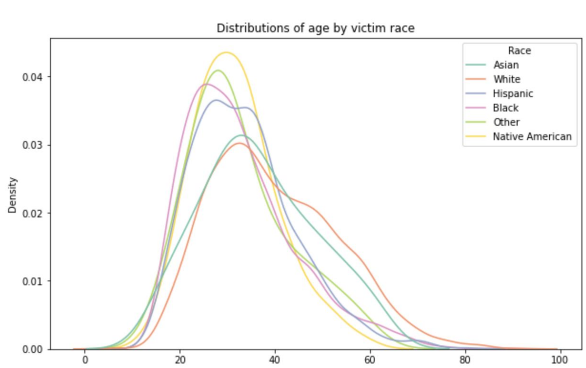


Figure 1: Visualizing fatal shooting victim demographics. Features include how the victim was killed, gender, race, signs of mental illness, threat level, whether they fled, and if the officer was wearing a body camera.

We next examined the ages of shooting victims and the relationship with race (**Figure 2**). The median age of shooting victims was ~30 years old, with the distribution skewed right. When splitting up the distributions by race, it became clear that some distributions were skewed further left (i.e., younger victims) than others. Black victims tended to be the youngest, with Hispanic, other, and Native American also tending to be younger. The ages of Asian and white victims were skewed furthest rightwards. This suggested that shootings disproportionately affect victims of different races. Using US census data to normalize the number of victims by the population of their race, Black victims were killed at a much higher proportion of their race than others.

A



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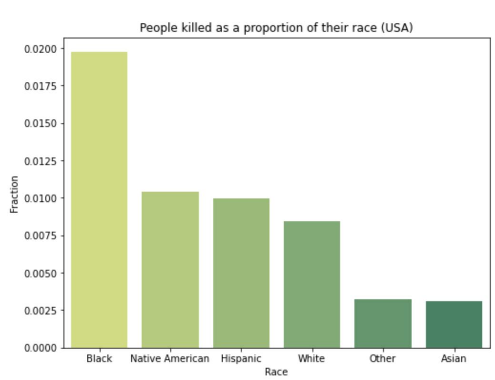

Figure 2: Distributions of age by race and shooting-related deaths as a proportion of race. A, kernel density estimations for distribution of fatal shooting victim age by race. **B**, fraction of shooting victims as a proportion of their race in the United States.

At the level of individual police departments, we analyzed the racial composition of both the police officers and the victims relative to the county in which the department is based. For each police department with at least five shooting victims, when comparing the fraction of non-white police officers to the fraction of non-white individuals in the county (**Figure 3A**), the vast majority of points fall below the unity line, indicating that police departments tend to be much whiter (69.5% white mean across the above included departments) than the communities they serve (53.2% white; note this may be lower than national average due to geographic biases in where departments are localized). In stark contrast, victims of police shootings are overwhelmingly less white than the racial composition of the county (**Figure 3B**). In comparing the racial composition of the police officers and the victims (**Figure 3C**), as expected from **Fig. 3A** and **Fig. 3B**, we see an even starker contrast: for nearly every police department analyzed (94.4%), the department is more non-white than the victims shot by that department.

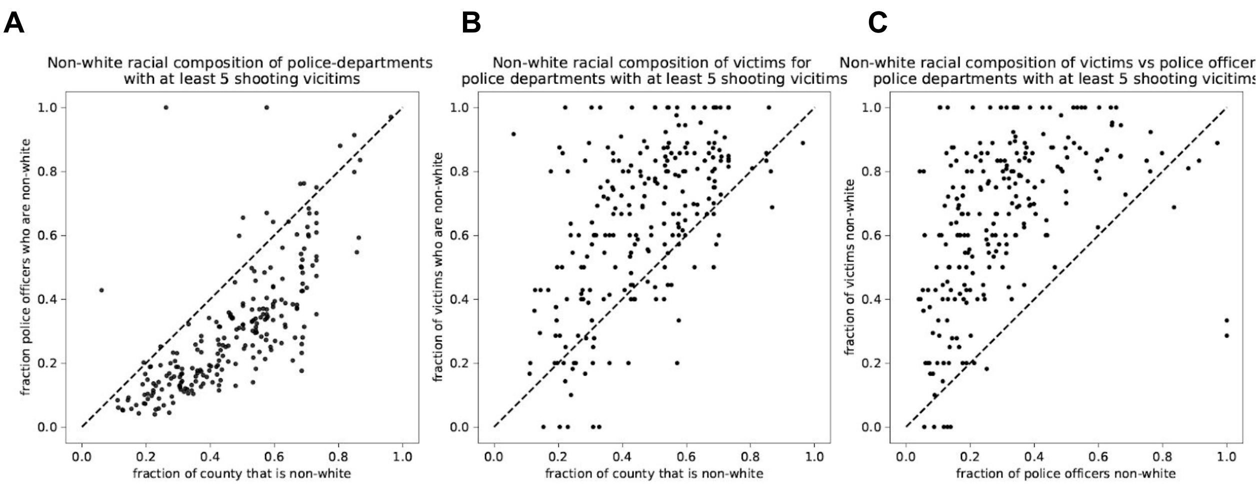

Figure 3: Comparing the racial composition of police department, victim, and county population.

The next angle from which we wanted to understand police violence was from police use of force and other policies. Regardless of whether a police department has adopted a use of force policy or not, the rate of fatal police shootings is relatively similar (**Figure 4**). This is interesting, as it does not align with what the use of force project reports. This may be due to the fact that their analyses were performed in 2016 when a small number of departments had implemented at least one of these policies. We aggregated the number of police shootings from 2015 to present day, and a significant portion of these police departments have implemented use of force policies since the original report was published.

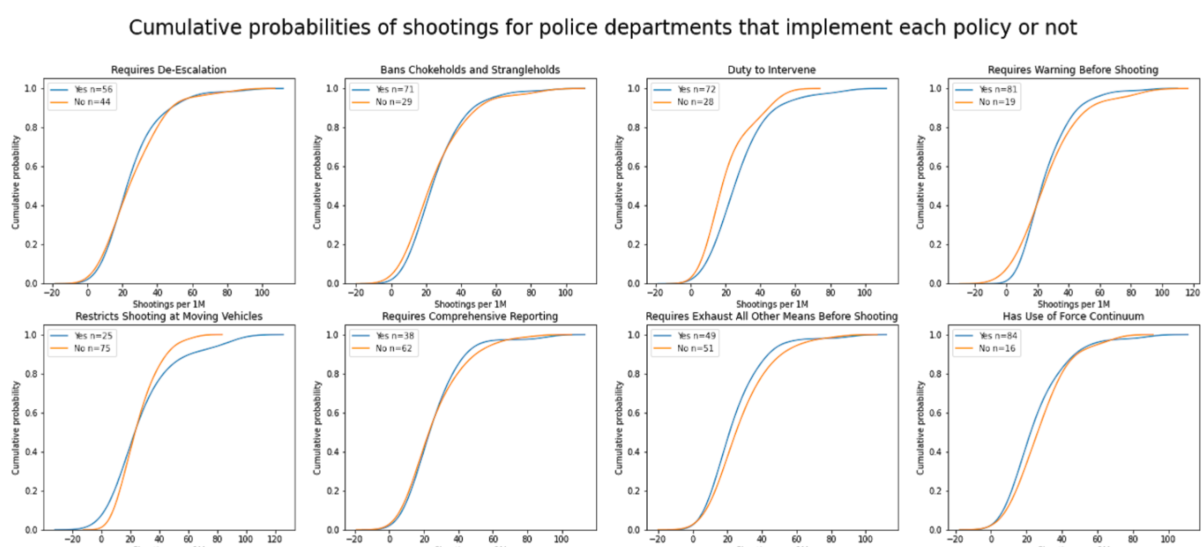

Figure 4: Cumulative probabilities of fatal police shooting rate in relation to policy implementation.

We also analyzed the percentage of fatal shootings in the WaPo dataset with body camera usage at the city level (**Figure 5A**; state level analysis shown in Milestone 3), and compared this with the rate of fatal shootings. There was a negative correlation between the rate of fatal police shootings and body camera usage. These correlations are inconclusive but suggest that: 1) cities where fatal police shootings occur frequently may lack policies/enforcement on body camera usage and appropriate use of force; 2) relatively low rates of fatal police shootings are associated with a range of values for the body camera usage, and this could be a result of high body camera deployment deterring police violence, or places lack the incentive to deploy body cameras due to few incidents of police shootings. We also calculated the percentage of body camera usage over time (**Figure 5B**), and compared the overall proportion of fatal shootings with body cameras used in the WaPo data with the proportion of police agencies having policies on body camera usage in LEMAS (**Figure 5C**). We found that although 40% of police agencies have policies on body cameras in 2016, only about 10% of the police officers involved had their body cameras on. Although the deployment of body cameras generally increases over time, the max usage is still about 15%, much lower than what police agencies claimed in 2016.

A **B** **C**

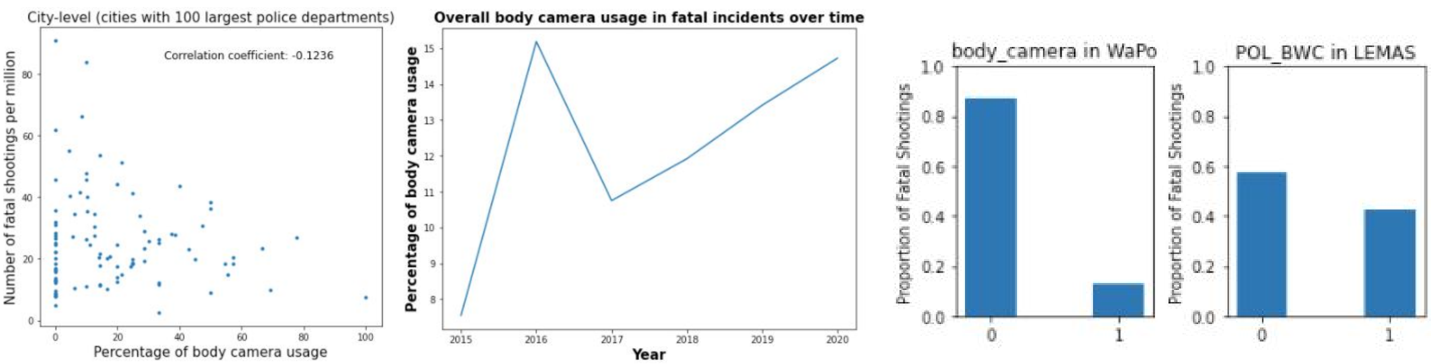

Figure 5: Body camera usage in fatal shooting cases and in police policy. A, body camera usage compared to rate of police shooting. **B**, body camera usage over time. **C**, overall body camera usage in reality compared to police policies.

Finally, we looked into how police training requirements in academy and in the field relate to the rate of fatal police shootings in cities (**Figure 6**; state level analysis shown in Milestone 3). At the city level, we see very weak correlations between training and rate of police training, which suggests that training hours may not be a good/reliable predictor for the rate of police shootings. We still kept these variables because they may still be useful for predicting other features of shooting victims, such as race.

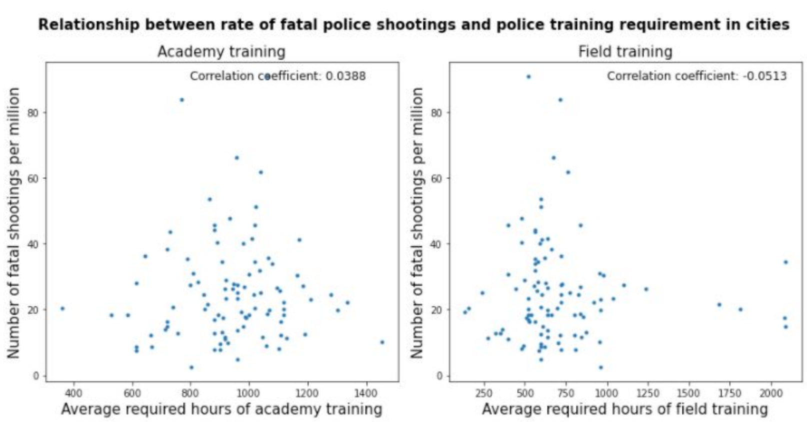

Figure 6: Relationship between police training requirements and rate of fatal police shootings.

Based on our EDA, we chose to pursue modeling of victims' race both based on police department demographics and policies and with victim demographics in order to try and isolate the influence of one versus the other.

Models

We did multi-class classification of race from two datasets. The variables in dataset (1) include demographics about the police department and their policies, along with county-level demographic data, which primarily come from LEMAS and census data (**Table 2**).

Variable	**Description** (see https://www.icpsr.umich.edu/web/ICPSR/studies/37323/variables)
race	Race of the victim
geo_Rural, geo_Suburban, geo_Undetermined, geo_Urban	The type of area that the shooting occurred in
body_camera	Whether the officer was wearing a body camera and it may have recorded some portion of the incident
POL_BWC	Agency has written policy or procedural directives on body-worn cameras
PERS_TRN_ACAD	Total hours of academy training required for new officer recruits
PERS_TRN_FIELD	Total hours of field training required for new officer recruits
POL_COMP_EXTINV	Written policy requiring that civilian complaints about use of force receive separate investigation outside the chain of command where the accused officer is assigned
POL_INV_INJRY	Agency requires an external investigation in the following use situations: use of force resulting in a subject sustaining serious bodily injury
POL_INV_DTH	Agency requires an external investigation in the following situations: use of force resulting in a subject's death
POL_INV_DCHG_GUN	Agency requires an external investigation in the following situations: discharge of a firearm at or in the direction of a person
PERS_CULTURE	Which of the following screening techniques are used by your agency in selecting new officer recruits? Assessment of understanding diverse cultural populations
PERS_CONFLICT	Which of the following screening techniques are used by your agency in selecting new officer recruits? Mediation/conflict management skills assessment
FRAC_WHITE, FRAC_BLACK, FRAC_HISP, FRAC_AMIND, FRAC_HAWPI, FRAC_MULTI, FRAC_UNK	For that police department, the fraction of officers who are white; Black; Hispanic; American Indian or Alaska Native, Non-Hispanic; Native Hawaiian or other Pacific Islander, Non-Hispanic; two or more races; unknown race
Hispanic, White, Black, Native, Asian, Pacific	The fraction of a given county that is: Hispanic, White, Black, Native American, Asian, or Pacific Islander
Poverty	The fraction of people in a given county who fall beneath the poverty line
Income	For a given county, the average income in dollars
Unemployment	For a given county, the unemployment rate (as a fraction, 0-1)

Table 2: Variables used for modeling in dataset1, with descriptions.

Dataset2 includes all of the features in dataset1 but with additional victim demographics (excluding race) from the WaPo dataset (**Table 3**).

Variable	**Description**
age	Age of the victim
signs_of_mental_illness	News reports have indicated the victim had a history of mental health issues, expressed suicidal intentions or was experiencing mental distress at the time of the shooting.
flee_Car, flee_Foot, flee_Not fleeing, flee_Other'	News reports have indicated the victim was moving away from officers
is_male	Gender of the victim
is_tasered_and_shot	Manner of death: whether the victim was tasered and shot (1) or only shot (0)

Is_armed_gun, is_armed_knife, is_unarmed, is_armed_other	Indicates that the victim was armed with some sort of implement that a police officer believed could inflict harm
threat_attack, threat_other, threat_undetermined	The general criteria for the attack label was that there was the most direct and immediate threat to life. That would include incidents where officers or others were shot at, threatened with a gun, attacked with other weapons or physical force, etc. The attack category is meant to flag the highest level of threat. The other and undetermined categories represent all remaining cases. Other includes many incidents where officers or others faced significant threats.

Table 3: Partial list of variables used in dataset2, with descriptions. Additional variables included but not shown are in **Table 2**.

For baseline models, we predicted race using the majority class (white; naive baseline train accuracy = 49.2%, test accuracy = 49.3%), or the majority race of the county where each fatal shooting occurred (baseline train accuracy = 55.7%, test accuracy = 57.4%). To predict race from the two datasets described above, we used the following models: K-NN classification, logistic regression, logistic regression with L1 regularization, decision tree, random forest, and AdaBoost. We performed preliminary model comparison and model selection by splitting the datasets into 80% training and 20% test, stratified by race, and standardized the data. For each model, we used 5-fold cross-validation and otherwise typically used default settings, although for tree-based models we used a maximum tree depth of 5. We chose to tune a random forest as our final model for both datasets (police department and county demographics, or with added victim demographics), as its performance was highest both on training and validation data for dataset1 and still high for dataset2 (68.6% and 66.2% for dataset 1, 70.0% and 66.9% on dataset 2; **Figure 7**). Given the accuracy for the random forest model was very similar to the best-performing logistic regression model for dataset2, we chose to use the same class of model across both datasets to make subsequent comparisons between the two datasets more interpretable.

A

Accuracies for dataset1

Model	CV Train Accuracy	CV Validation Accuracy
KNN	0.705	0.594
Logistic Regression	0.654	0.646
Lasso-Logistic Regression	0.655	0.648
Decision Tree (max_depth=5)	0.675	0.635
Random Forest (max_depth=5)	0.686	0.662
AdaBoost	0.508	0.499

B

Accuracies for dataset2

Model	CV Train Accuracy	CV Validation Accuracy
KNN	0.721	0.600
Logistic Regression	0.678	0.669
Lasso-Logistic Regression	0.678	0.668
Decision Tree (max_depth=5)	0.680	0.649
Random Forest (max_depth=5)	0.700	0.669
AdaBoost	0.508	0.489

Figure 7: Tables with the cross-validation training and validation accuracy for each model fit on two separate datasets. A, model accuracies fit on dataset1. **B**, model accuracies fit on dataset2.

We then used a cross-validated grid search to determine the best hyperparameters for random forest fitting on the training data, and then predicted victim race on the test data.

Results

On the test data for dataset1 and dataset2, the test accuracy for our final random forest classifiers (dataset1: maximum depth = 7, estimators = 500; dataset2: maximum depth = 7, estimators = 500) was 64.0% and 65.7%, respectively, demonstrating that these models performed well above the baseline models (49.2% and 56%) for predicting race of the victims. The accuracy for the dataset2, which contains all of the predictors from dataset1 but also victim features, was higher than for dataset1, which indicates that there was additional predictive power from including the extra victim-related predictors. We then examined the permutation feature importances of the models for the two datasets (**Figure 8**).

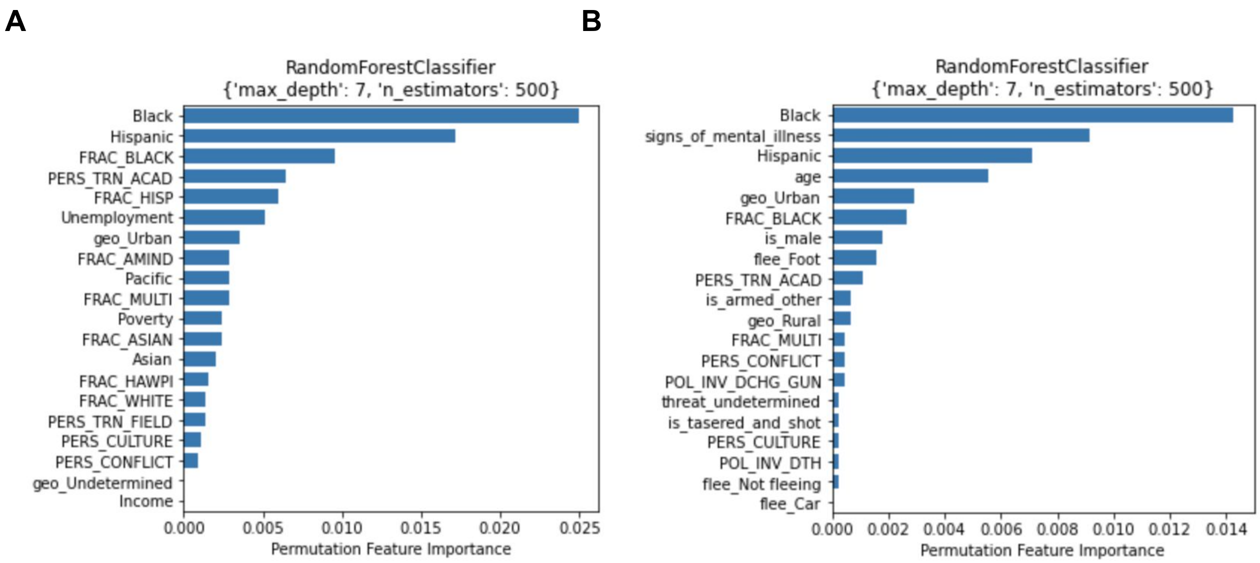

Figure 8: Permutation feature importances for random forest models for dataset1 (A) and dataset2 (B).

For dataset1, which only includes predictors about the police department demographics and policies in addition to county-level demographic features, the top three most important features include `Black`, `Hispanic`, `FRAC_BLACK`, and `FRAC_ASIAN` (**Fig. 8A**), all of which reflect the demographic makeup of the county or county's police force. The feature with the fourth highest importance was `PERS_TRN_ACAD` (total hours of academy training required for new officer recruits), which is interesting given that it was higher than many other demographic-related variables.

If there are no biases in terms of the race of shooting victims, then the added variables about victim demographics in dataset2 should not be important features. However, as already observed in our EDA, we saw that the distributions of victim age by race were very different. Specifically, the peak of the distribution for age of Black victims is shiftest youngest out of all races. This is consistent with the model fitted on dataset2, as `age` was the fourth most important predictor of victim race (**Fig. 8B**). Interestingly, `signs_of_mental_illness` was the second most important feature, suggesting that whether the victim had a history of mental health issues, expressed suicidal intentions, or was experiencing mental distress at the time of the shooting was also predictive of race (more likely a white victim). Most of the remaining predictors in the top 20 were still reflective of local demographics.

We also examined the feature importances and beta coefficients for the logistic regression models with lasso regularization, as the accuracy for these models on dataset1 and dataset2 were similar to the random forest models. We found that the top feature importances/coefficients were similar to those we found using the random forest models (data not shown).

From our EDA, we found that most victims were predominantly white (49.2%), Black (29.5%), or Hispanic (17.4%). Asian and Native American victims only comprised 1.58% and 1.20% of all victims, respectively. Given this significant class imbalance, our final models may simply ignore and poorly predict the minority classes of Asian and Native American victims. This is exactly what we observe in both final random forest models where they do not predict Asian and Native American victims in the test set (**Figure 9**). In the future, we may want to implement SMOTE to synthetically generate data for the minority classes in order to improve our model performance.

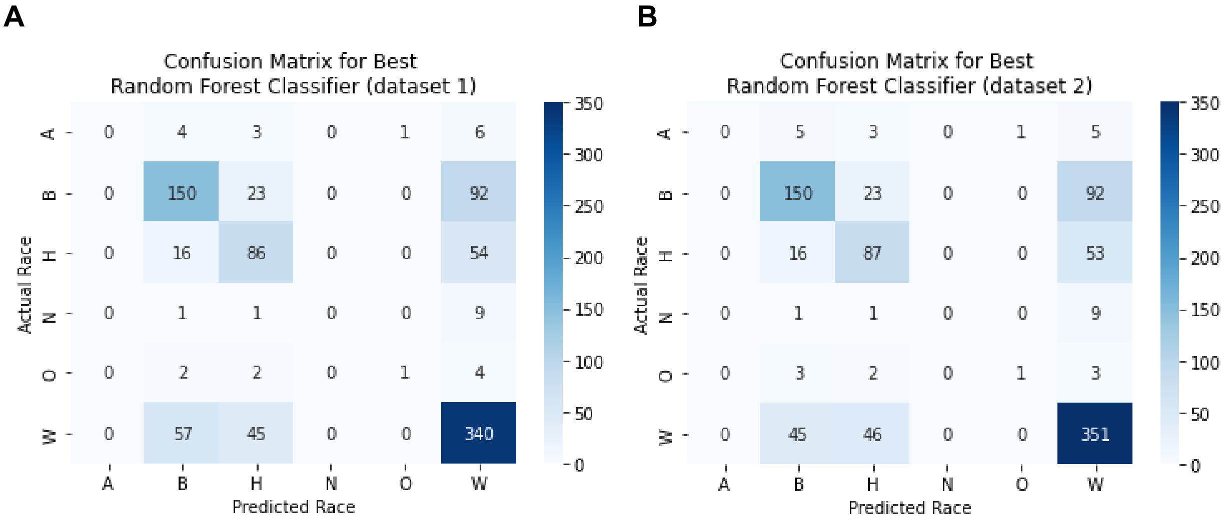

Figure 9: Confusion matrices for random forest models for dataset1 and dataset2. Color represents count.

To understand how some of the top features were related to the response variable, we plotted the probability of predicting each race as a function of each predictor, by systematically varying the predictor of interest while keeping all other variables constant (**Figure 10**). As `Black` and `FRAC_BLACK` increase, which are the fraction of the county and officers in the police department that are Black, respectively, we see that the probability of predicting the victim as black also increases (**Fig. 10A,B**), as expected. However, it is interesting to note that predicting a victim as Black does not follow the population demographics, and instead shooting victims are more likely to be Black than would be expected from the demographics of the county or police force.

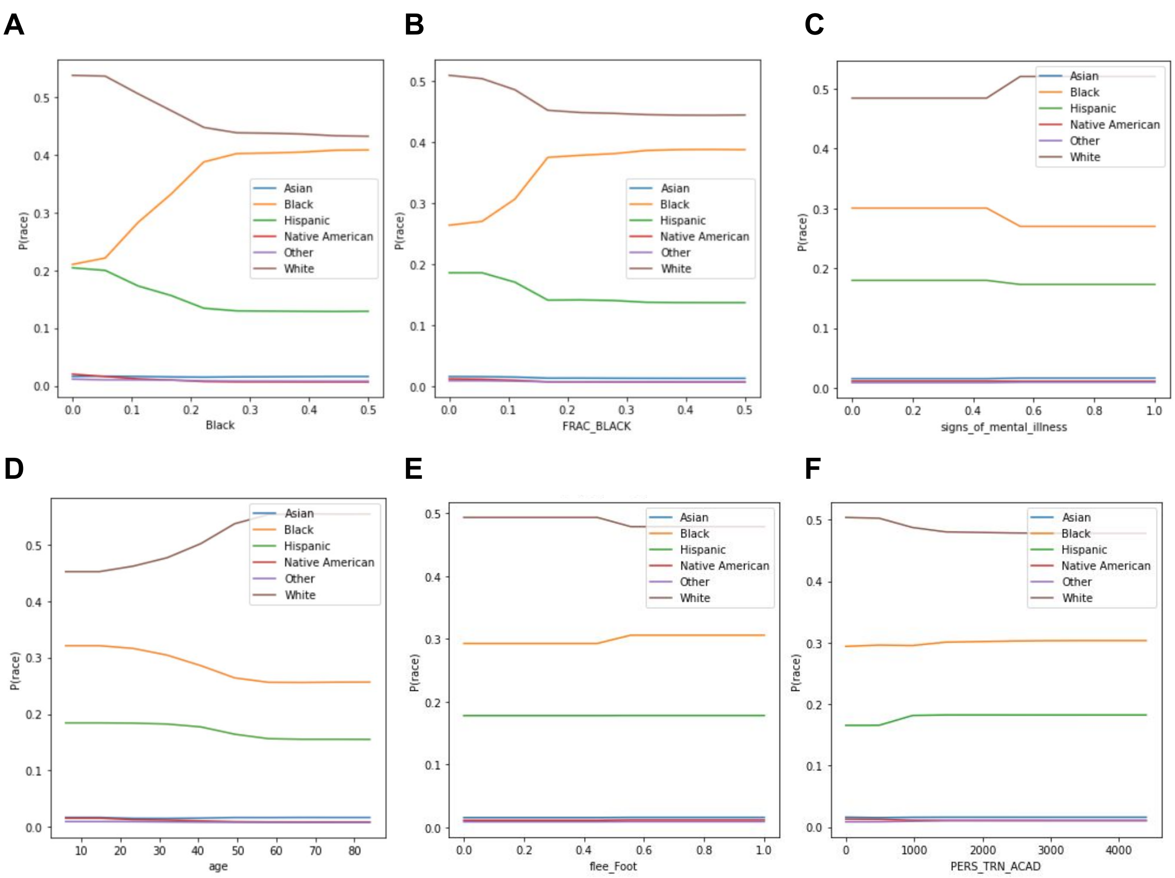

Figure 10: Probability of each predicted race as a function of selected predictors from dataset2.

When looking at whether the victim showed signs of mental illness (note that this is actually a binary variable), Black victims who showed signs of mental illness were less likely to be predicted as Black, whereas the opposite trend holds for white victims (**Fig. 10C**). We also see that with increasing age, a victim has a higher probability of being white (**Fig. 10D**), which highlights our EDA findings that the age distributions of victims by race were very different from one another. Black victims who were fleeing on foot were more likely than those not fleeing to be predicted as Black (**Fig. 10E**). Finally, surprisingly, more academy training is associated with more racial bias against Black and Hispanic people in fatal shootings (**Fig. 10F**).The effect size is small, possibly due to the tendency of random forests to distribute feature importance across more variables. More data and studies on police training are needed to elucidate the direction of causality of this relationship.

Discussion

Modeling summary; strengths, limitations, and future directions

We used random forest models to predict fatal shooting victim race from two datasets: one that included predictors about the police department associated with the shooting (i.e., their demographics and policies) and demographics of the county in which the shooting took place, and a second that included all of the predictors in the first dataset but also including features about the victim (e.g., age, whether they showed signs of mental illness, gender, among others). We found that both models performed with higher accuracy than naive baseline models, with the second model performing slightly better. Across both models, features related to county-level and police department racial demographics were the strongest predictors of victim race. Interestingly, however, the total hours of police training for new recruits was also a strong predictor of victim race across both models, which could suggest that there should be standardized requirements for the minimum number of hours of academy training as well as the content. In addition, whether the victim was showing signs of mental illness or had a prior history of mental illness was also very predictive of victim race, which could provide some support for requiring additional training in de-escalation policies and identifying signs and symptoms of mental illness.

A fundamental limitation of our modeling approach is that the data available on police violence and shooting victims that we used is limited both in terms of number of shootings and the years over which the data were collected. In addition, a limitation of our random forest models is that although they had high performance on the test set and distribute predictive power to more parameters and decorrelate trees to reduce the variance of predictions, this can make relative importance between variables more difficult to interpret (e.g., compared to logistic regression models). Furthermore, studies have found that permutation feature importance can overestimate the importance of correlated features[1], especially for tree-based models that interpolate badly for unseen data; we could use SHAP values or other approaches to evaluate feature importance. Future work could also compare the coefficient values from logistic regression, as well as examining which variables are nonzero when using L1 regularization. In addition, accuracy of all of the models we tested appeared to reach a maximum at ~70%; however, our goal was not to have a perfect model that predicts race, but instead to see if the predictors used could shed light on the relationship between race and police violence. Another potentially interesting future direction to take once more years of data are available would be to see whether predicting race from the features we used in our modeling becomes more difficult over time, which could suggest that racial bias is decreasing. Finally, all of our modeling was done at the county level, but given more data, it could be informative to do similar analyses at the city or state levels.

Additional datasets and broader implications/impact

Initially, we explored the police use of force dataset from Campaign Zero in EDA, and generally did not see a drastic difference in the rate of fatal police shootings between police departments with and without the policies in question. We decided not to incorporate the use of force dataset in the modeling section since it only contains information on 100 city police departments, and for policies that did seem to make a difference

[1] Strobl, Carolin, et al. “Conditional Variable Importance for Random Forests.” *BMC Bioinformatics*, vol. 9, no. 1, 2008, doi:10.1186/1471-2105-9-307.

(de-escalation, use of force continuum, duty to intervene) we found similar policies in the more comprehensive LEMAS dataset.

Although the LEMAS dataset contains rich information on police agencies, we are still unable to answer important questions on police violence, such as the changes in police killings over time or the number of fatal police shootings normalized by the number of police encounters for each race. Such data are critically missing, and this lack of timely update is evident in the fact that the most recent LEMAS data is a snapshot of 2016, but only released in 2020. A centralized and standardized database of police-related information such as the National Justice Database[2], would allow the public to easily access information essential for evaluating police performance and hold them accountable (we did reach out to the National Justice Database requesting more data, but did not hear back from them). For example, we noticed a striking gap between policy on paper and implementation in reality in *The Washington Post* shootings dataset, where for many victims the police officer had body cameras off, despite their police agency having written policy on body cameras. Having more comprehensive information on not only police policies but also their enforcement in a publicly-accessible database is vital in order to assess police violence and motivate police reform.

While fatal police shootings are fairly easy to track, data on other forms of police behavior and police violence may be even more informative from a modelling perspective. Shootings are relatively rare and represent a tip of the iceberg of police violence and racial bias. Data on events such as stop, question and frisk, arrests, and non-fatal violence would provide a much greater number of samples and lower noise when comparing different geographical areas. We chose not to examine changes in the number of police shootings over time, as these events have remained relatively stable over the past 5 years in national aggregate as shown in the *Washington Post* fatal shootings dataset. Additionally, the sporadic nature of shootings on a local level makes it hard to estimate the rate of change of police violence in individual police departments over time. Other measures of police behavior would not have this issue and therefore could be interesting to examine in relation to department policies and policy changes.

When applying data science to such a politically charged topic such as race-based police violence, making the limitations of models clear, as well as being careful about any claims, is of the utmost importance so that the results are not misinterpreted. The 2019 article "Officer characteristics and racial disparities in fatal officer-involved shootings" examined the relationship between the race of officers and victims involved in a fatal-shooting[3]. The study found no evidence that the race of the officers was related to the likelihood of the victim being a minority and the authors concluded that racial diversity on police forces would have limited benefit in reducing police violence -- a claim that was widely reported by the media. After criticism from other researchers that these claims were misleading, the paper was ultimately retracted. However, some critics of racially-related police violence still try to claim the retraction was politically motivated rather than because of methodological flaws that led to incorrect conclusions. This example serves as a cautionary tale about using modeling for social issues, as the work can be cited, justifiably or not, to drive policy decisions.

In summary, this project has shown us that implementing policies at not just the local, but federal levels, for detailed tracking of police behavior, collecting data, and holding police departments accountable for any violation of their policies is a step in the right direction. Despite limited data, over the years it has become increasingly clear that something needs to be done. Evidence-informed actions that have already been taken to modify use-of-force policies and require additional police training are beginning to drive meaningful change in reducing police violence.

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[2] "National Justice Database." *Center for Policing Equity*, policingequity.org/what-we-do/national-justice-database.

[3] Johnson, David J., et al. "Officer Characteristics and Racial Disparities in Fatal Officer-Involved Shootings." *PNAS*, National Academy of Sciences, 6 Aug. 2019, www.pnas.org/content/116/32/15877.