 CS109A: Final Project Milestone 3

Group #39 - Police Violence in the US

Team Members: Chika Okafor, Vasco Meerman, Matthew Parker, and David Koupaei

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# A description of the data

After researching many available crime datasets, the team quickly realized that almost all projects referenced one of two key datasets: [Mapping Police Violence](https://mappingpoliceviolence.org/) and the [Washinpost's repo](https://github.com/washingtonpost/data-police-shootings). The team is confident these are the most thorough and trustworthy datasets publicly available.

**Washington Post:** In 2015, The Post began tracking more than a dozen details about each killing — including the race of the deceased, the circumstances of the shooting, whether the person was armed and whether the person was experiencing a mental-health crisis — by culling local news reports, law enforcement websites and social media, and by monitoring independent databases such as Killed by Police and Fatal Encounters.

**Mapping Police Violence:** This information has been meticulously sourced from the three largest, most comprehensive and impartial crowdsourced databases on police killings in the country: FatalEncounters.org, the U.S. Police Shootings Database and KilledbyPolice.net.

**Selection:** The mapping police violence dataset has more predictors and data entries which could still be of interest for this analysis, but it also has some NaN values and incomplete data. Washington Post sources their data from the mapping police violence dataset, but they cleaned the data more completely making it more useful for many required comparisons in this investigation. Therefore, the best data source to answer the proposed analysis questions is the Washington Post dataset.

Key predictor and response variables:

|  |  |  |
| --- | --- | --- |
|  | Washington Post | Mapping Police Violence |
| Size | * 17 columns * 5716 rows | * 27 columns * 8507 rows |
| Response | * Count of violent incidents | * Count of violent incidents |
| Useful Predictors | * Date * Manner of death * Armed? * Age * Gender * Race * State * Signs of mental illness * Threat level * Flee * Longitude/Latitude | * Victim's age * Victim's gender * Victim's race * Date of Incident (m/d/y) * State * Cause of death * Death justified? * Criminal Charges? * Symptoms of mental illness? * Unarmed? * Alleged Weapon * Alleged Threat Level * Fleeing * Geography |

*Table 1: Predictor and Response Variables Reviewed*

|  |  |  |
| --- | --- | --- |
| Raw Predictors | Data Type | Description |
| *date* | Timestamp | Specific time of fatal police shooting incident |
| *Manner of death* | Classification object | How did victim die? (overwhelmingly shot) |
| *armed* | Classification object | With what type of weapon was the victim armed |
| *Age* | Integer | Age in years |
| *gender* | Classification object | Male/Female classification |
| *Race* | Classification object | Racial demographic classifier |
| *state* | Classification object | US State classification |
| *Signs of mental illness* | Boolean | Did Victim show signs of mental illness [y/n] |
| *threat level* | Classification object | Was there deemed to be a threat of violent action |
| *Flee* | Classification object | Did the victim flee the scene? |
| *Longitude/Latitude* | Float64 | Location of the incident |

*Table 1: Raw Predictors Reviewed*

Note that ‘id’, ‘Name’, and ‘is\_geocoding\_exact’ were removed as they were not required for modeling, and a body\_camera classifier was eliminated due to lack of reliable data.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Derived Predictors | Data Type | Derived From | Description | Rationale |
| *Pop density* | Float64 | lat/long location  zip code information | Number of people per square mile | Crime might be correlated to pop density and thereby also correlated with victim’s race |
| *Urban* | Class object | population Density | Urban, Suburban, or Rural | Population density as a categorical variable instead of a continuous variable.  This would allow us to understand in the Feature Importance analysis whether a particular category of urban center impacted the likelihood of the police shooting victim to be black |
| *Party* | Class object | State, Date (Year)  voting records by state | Democrat or Republican favored state | There may be greater racial animus in areas where the political affiliation is more solidly Red.  This may translate to measurable differences in the incidence of black victims from police shootings |
| *Median Income* | Float64 | lat/long location  zip code information | Median income of residents | Low-income areas often map to areas with a greater proportion of minorities.  Hence, one might expect that income would be inversely related to the likelihood of a black victim from police shooting |

*Table 2: Supplemental Predictors Reviewed*

# EDA Methods

The EDA section was performed by all team members to ensure a diverse set of observations and informed conversations moving into the modeling and results section of the project.

The general flow of the investigation was:

* Review and Describe data
  + Starting with many available sets, whittle down to only the most useful data (*research*)
  + Finalize dataset most capable of answering initial project questions (*Washington Post set*)
* Take a deeper look at distribution of each predictor variable
  + Make sure data is sensible and complete, clean as needed (*info(), value\_counts, histograms, pairplots*)
  + Make sure variables are informative (appropriate distribution of observations across values with *hist*)
* Dig in further to selected datasets with initial look at trends
  + Total count of incidents by race, time, and other predictors (*bar plots and histograms*)
  + Sample means, standard deviations, aggregate by year, by Geography (*barplot, try map plot*)
  + % of incidents by other predictors:
    - by threat level, allegedly armed, by race, by fraction of US population, and mental health
* Review Correlations
  + By race, gender, state, age, and other predictors like: (*heatmap plot*)
    - With and without threat level, flee, signs of mental illness, unarmed (*various plots*)
    - Allegedly armed/unarmed and threat level (*various plots*)
* Perform additional visualizations gaining deeper insights of predictors (*Scatterplots, swarm plots, histograms*)
  + Outcomes, by race (criminal charges, official disposition, etc.)

# Visualizations and Data Summary

This analysis is broken down into initial views and then some more informative visualizations

|  |  |  |
| --- | --- | --- |
| *Fig 1: Incidents over time* | *Fig 2: Incident by race and location* | *Fig 3: WaPo predictor pairplot* |
|  |  |  |
| *Fig 4: Correlation of predictors* | *Fig 5: Geographic distribution of incidents* | *Fig 6: Racial Distribution over Time* |

# Revised project question based on insights gained through EDA

Initial problem questions from Milestone 2:

1. How overwhelming is the evidence of discrimination in police violence?
2. Are there geographic differences in these injustices?
3. Has the frequency of police violence towards the citizens it tries to protect increased over the last 4 years?

EDA was very informative to shaping our thoughts and ideas about what questions would result in the most impactful analysis. The team compressed into two updated questions.

Modified questions:

1. Is the (population-weighted) incidence rate of police shootings different for white vs. black victims, after controlling for observable characteristics?
2. How has the population-weighted incidence rate of police shootings shifted over the period 2015 to 2020?
   1. By race of victim
   2. By geographic region

# A baseline model

For both of our modified questions, we will restructure the Washington Post dataset, so that each row corresponds with a unique state and year. For each state-year, we will construct two outcome variables: (1) the total black civilian shootings per capita and (2) the total white civilian shootings per capita. We will also add various control variables, including: (1) state median income level; (2) state population; and (3) state violent crime rate.

* **To answer Modified Question #1**, we will use a Paired T-Test, comparing the means for total black shootings per capita and total white shootings per capita
* **To answer Modified Question #2**, we will fit the following Linear Regression Model:
  + where denotes with the total shootings per capita in state *s* during year *t* for race *r*. This expression will be evaluated for when race is white and when race is black.
  + denotes with state fixed effects
  + denotes with time fixed effects
  + denotes the year. As 2015 is omitted from the regression specification, the coefficients are normalized such that the 2015 values are set to 0
  + are a series of state and year controls
  + The coefficient of interest is , which demonstrates the relative impact on the outcome variable for each subsequent corresponding year.