



# Policing the Police

# Our Dataset

**Merged from the largest databases of police violence in America:**  
Mapping Police Violence, Deadspin, The Washington Post

**Consists of all recorded police killings from 2013 - 2020**

## **Individual-Specific Variables**

- Age
- Gender
- Race

## **Location-Specific Variables**

- State
- City
- County
- Geography type: Rural/ Urban/ Suburban

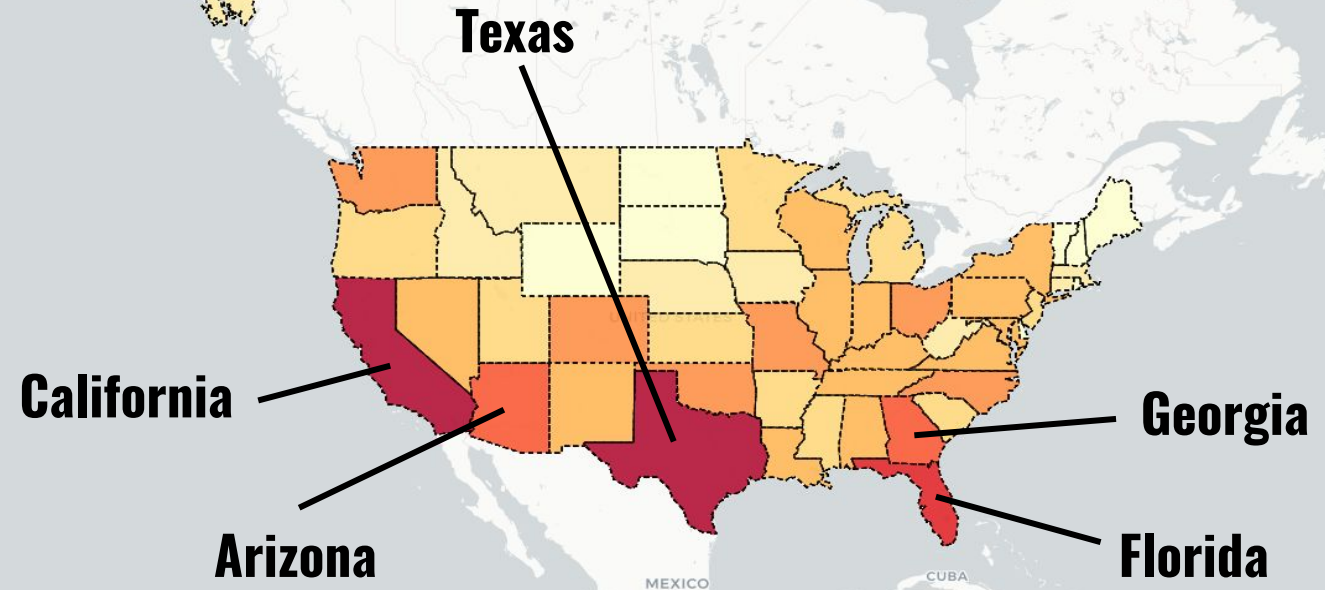
## **Circumstance-Based Variables**

- Weapon on victim
- Whether the victim was perceived to be a threat
- Whether the victim suffered from mental illness
- Cause of death
- Description of death
- Whether the police killing was justified under law
- Police agency responsible



# Total Police Killings by State (From 2013 - 2020)

## Top 5 States









# Rate of Police Killings (Per Million)

## Top 5 States

**Alaska**

**Nevada**

**Arizona**

**New Mexico**

**Oklahoma**



# Rate of Police Killings (Per Million)

## Bottom 5 States

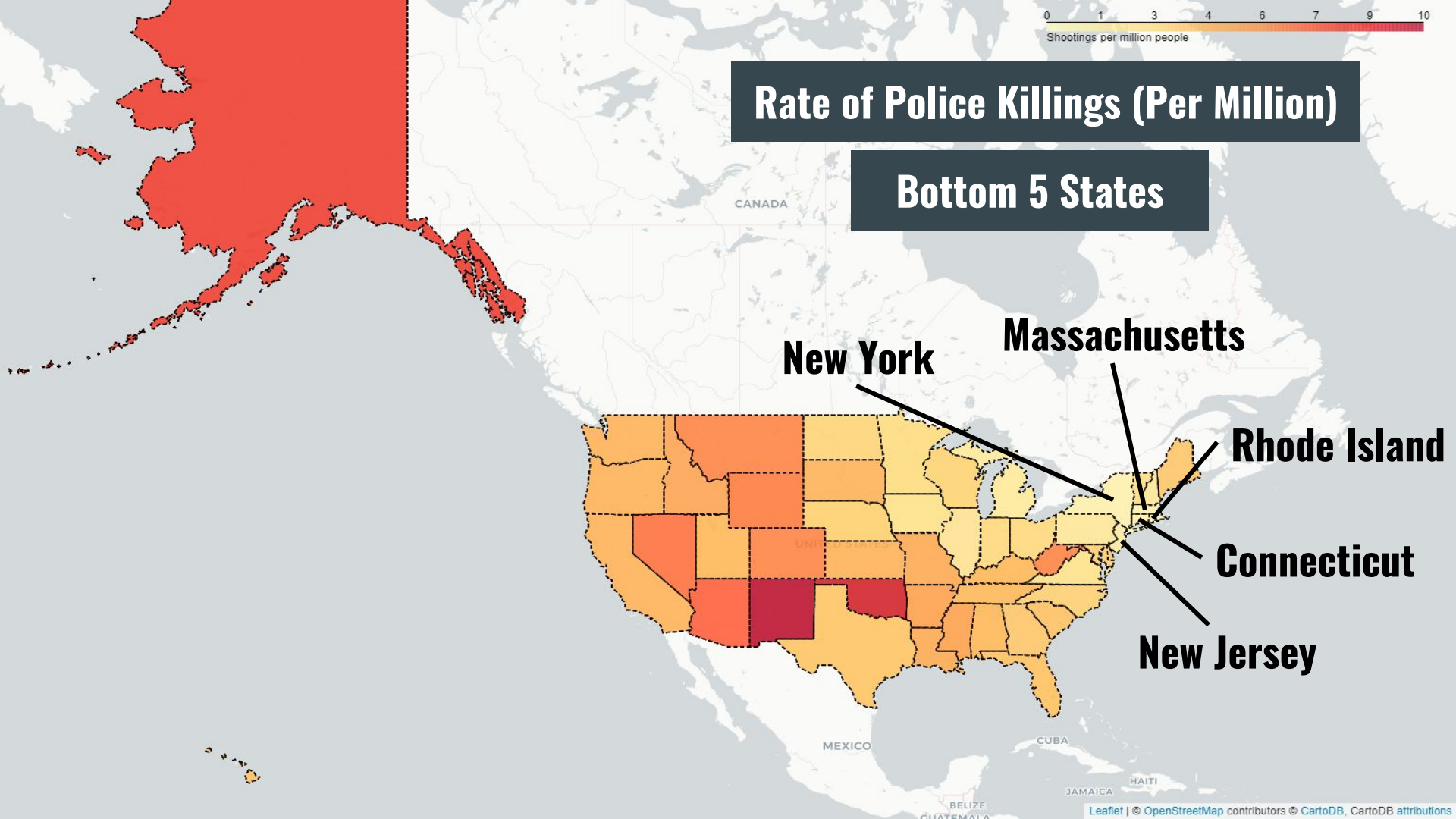
New York

Massachusetts

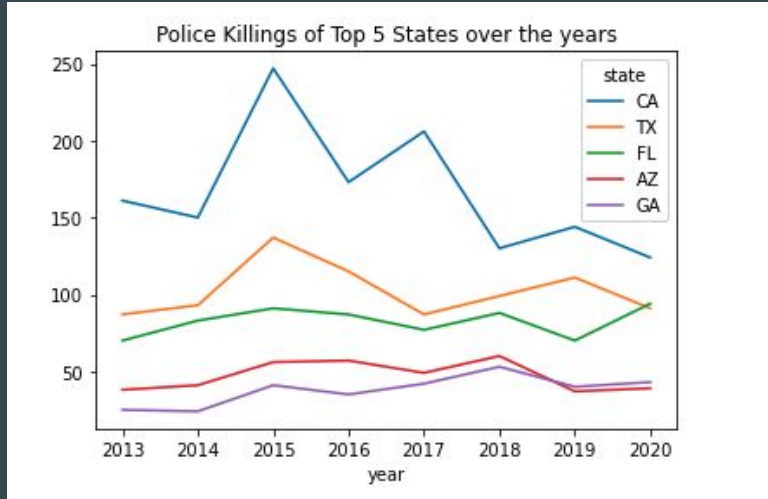
Rhode Island

Connecticut

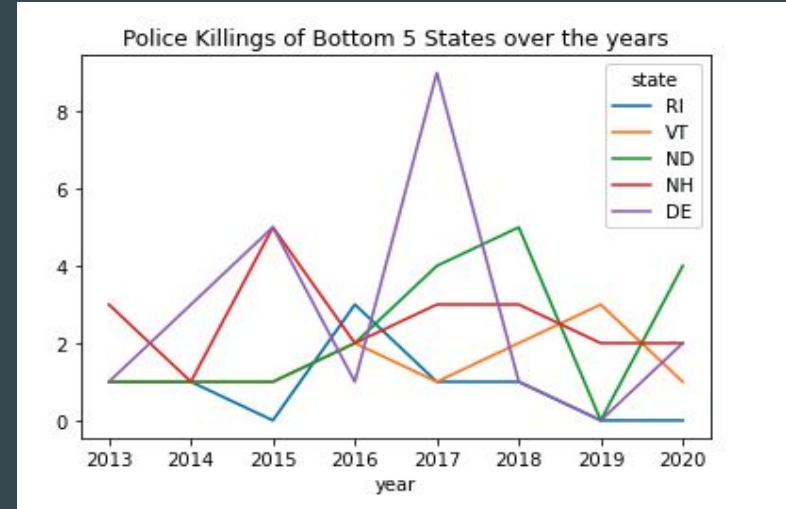
New Jersey



# How Have Police Killings Changed Over Time?

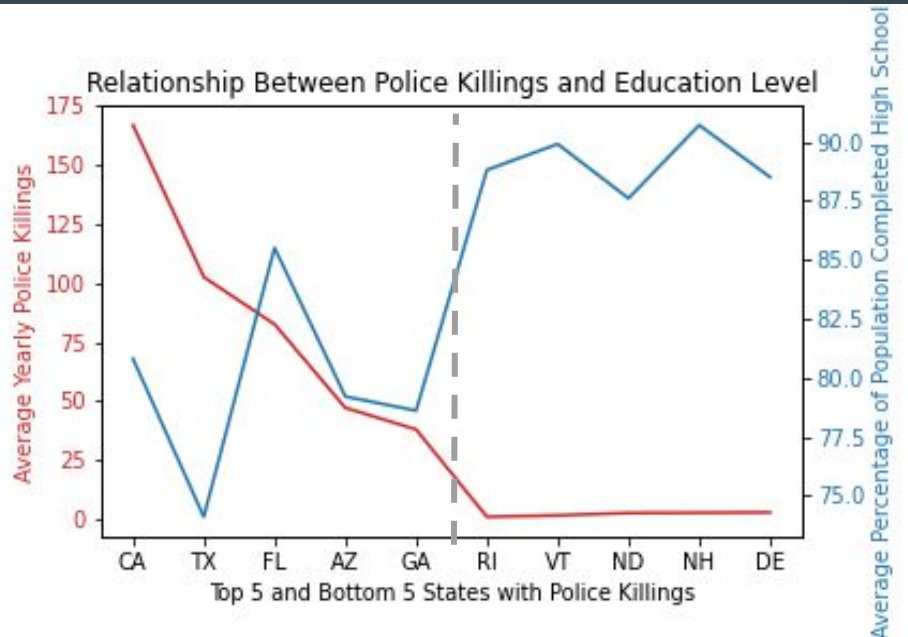


**Small fluctuations over the years:  
Police violence has not improved in  
these Top 5 states!**



**Bottom 5 states have stayed  
relatively low over the years**

# Why Do States Differ In Police Killings?



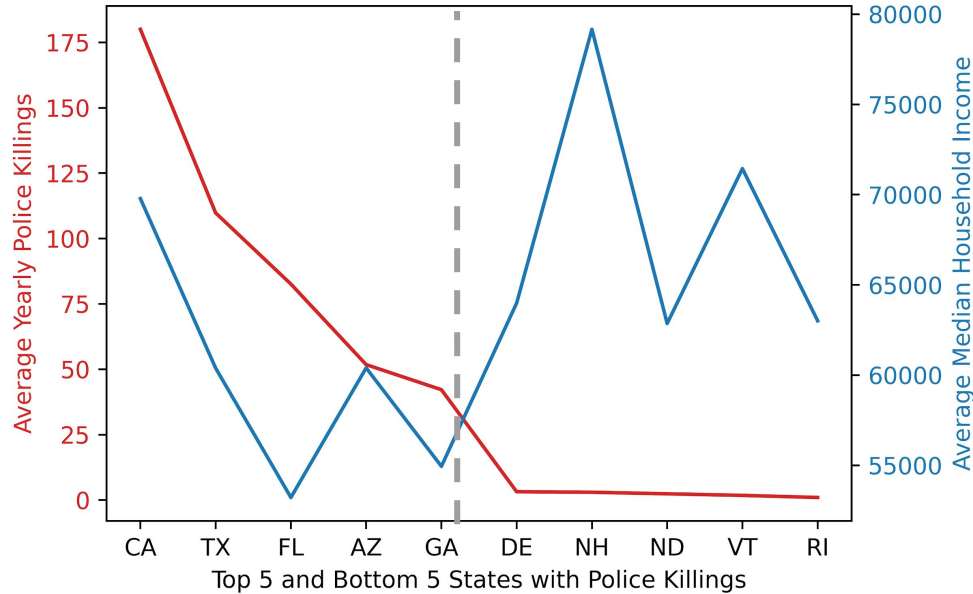
**Negative Correlation:**  
Higher education level = Lower police killings

**Different Education Levels**



# Why Do States Differ In Police Killings?

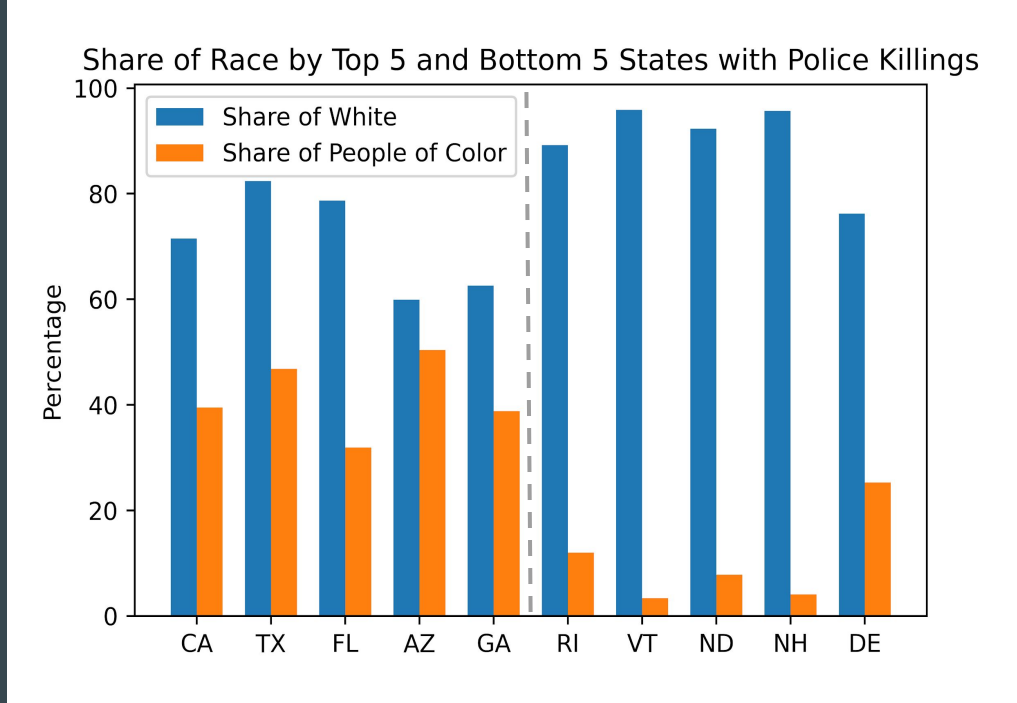
Relationship Between Police Killings and Median Household Income



**Negative Correlation:**  
Higher income level = Lower police killings

**Different Income Levels**

# Why Do States Differ In Police Killings?



**Positive Correlation:**  
Higher share of people of color  
= Higher police killings

**Different Population Racial Makeup**

# Why Do States Differ In Police Killings?

Create 3 new state-level features:

- 1) ***state\_education\_level***: Proportion of population completed high school in each state
- 2) ***state\_log\_income***: Log of median household income in each state
- 3) ***state\_white\_share***: Share of Whites in each state

Creating New Features Using Correlations Observed

[illegible]

### Circumstance 1: Police killings inside residences

## Topic Modelling (LDA) Using *Description of Death* Column



# Circumstances Surrounding Police Killing



Circumstance 2: Police killings involving vehicles,  
where victim is fleeing

Topic Modelling (LDA) Using *Description of Death* Column

# Circumstances Surrounding Police Killings

Topic 1: Police killings inside residences

Create new binary feature, ***home\_involved***

Topic 2: Police killings involving vehicles,  
where victim is fleeing

Create new binary feature, ***vehicle\_involved***

Create new binary feature, ***was\_fleeing***

Creating New Features using Text Mining Results

# How Were Victims Killed?

Group into 3 most common causes of death:

- By gunshot
- By taser
- By physical violence (Beaten/ Physical Restraint/ Asphyxiation/ etc)



Create 3 new binary features:

- 1) ***killed\_by\_gunshot***
- 2) ***killed\_by\_taser***
- 3) ***killed\_by\_physical\_violence***

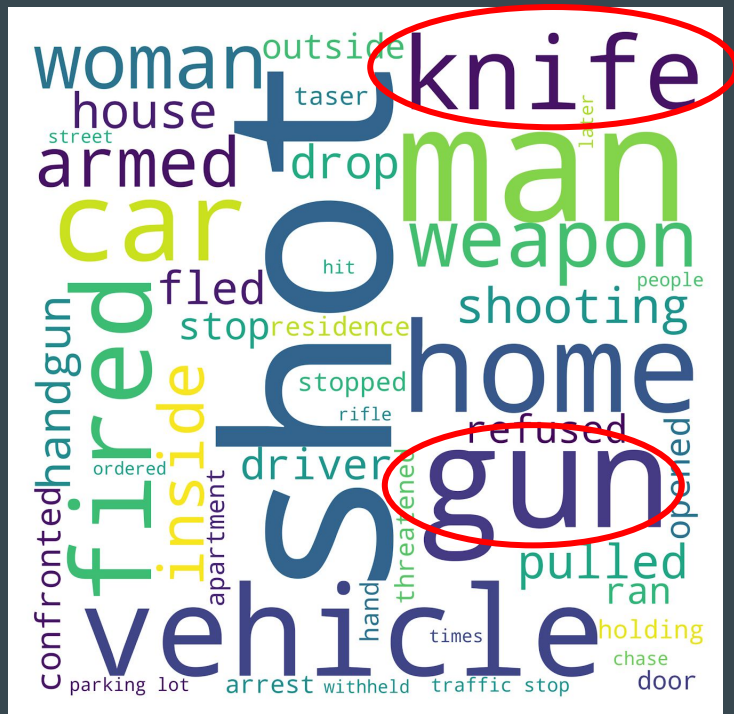
## Analysis of Cause of Death Column

Gunshot	6982
shot	1437
Gunshot, Taser	237
Taser	221
shot and Tasered	88
Beaten	29
Vehicle	27
Physical Restraint	23
Tasered	13
Physical restraint	9
Asphyxiated	8
Gunshot, Police Dog	5
Other	5
Pepper Spray	4
Taser, Physical Restraint	2
Gunshot, Pepper Spray	2
Taser, Pepper spray, beaten	1
Baton, Pepper Spray, Physical Restraint	1
Bean bag	1
Beaten/Bludgeoned with instrument	1
Bomb	1
Chemical agent/Pepper spray	1
Gunshot, Beanbag Gun	1
Gunshot, Bean Bag Gun	1
Gunshot, Stabbed	1
Taser, Pepper Spray, Beaten	1

# Data Transformation to Create Meaningful Features

# Were Victims Armed?

### Analysis of *Description of Death* Column



## Analysis of Weapon On Victim Column

Allegedly Armed	5383
Unarmed/Did Not Have an Actual Weapon	1082
gun	886
Unclear	612
Vehicle	505
knife	229
unarmed	103
toy weapon	45
undetermined	40
vehicle	35
unknown	20
sword	9
machet	9
baseba	7
metal	7
gun an	6
hammer	5
hatchet	5
ax	4

We already created a new feature named *vehicle\_involved* earlier

Create 2 new binary features:

- 1) *armed\_with\_gun*
- 2) *armed\_with\_knife*

We already created a new feature named *vehicle\_involved* earlier

## Create 2 new binary features:

- 1) ***armed\_with\_gun***
- 2) ***armed\_with\_knife***

# Data Transformation to Create Meaningful Features



# Target Encoding: For Categorical Features With Many Levels

Categorical features encoded:

- 1) ***state***: Consists of 50 unique states
- 2) ***police\_agency***: Consists of 2866 unique police agencies

**What is Target Encoding:**

Encode each level with the mean of the target variable for that level

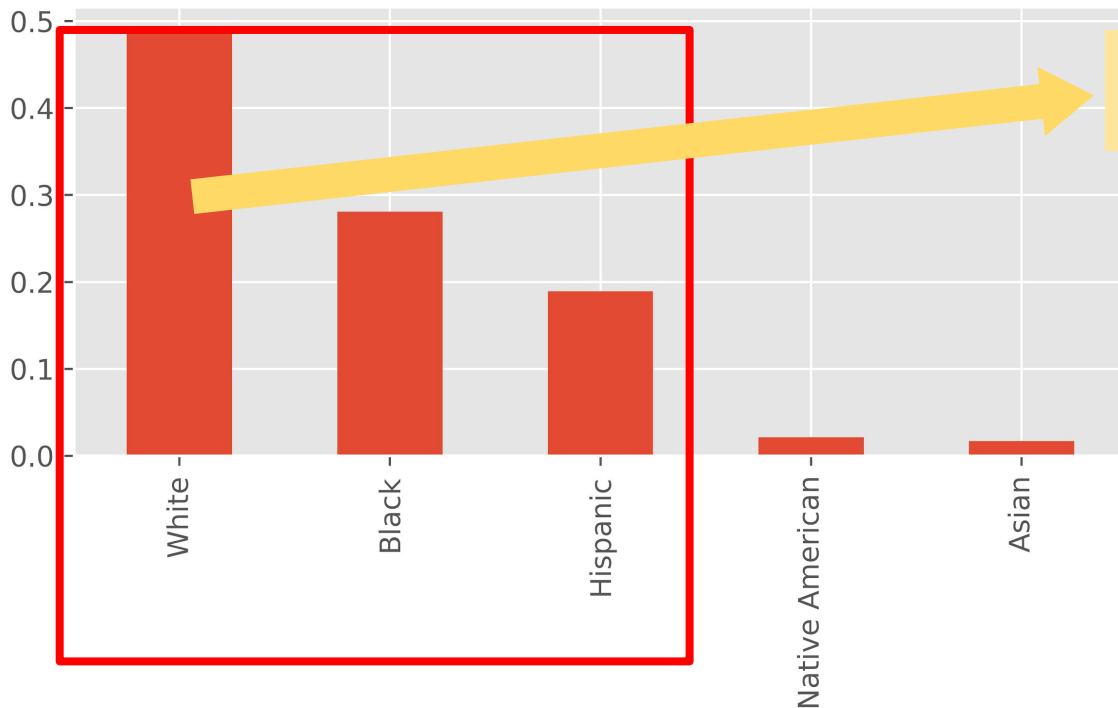
**Advantage over One-Hot Encoding:**

Does not add to dataset dimensionality

## Encoding Categorical Variables

# Inspiration for Machine Learning: Does Race Affect How Police Kill?

Proportion of Races Amongst Police-Killing Victims

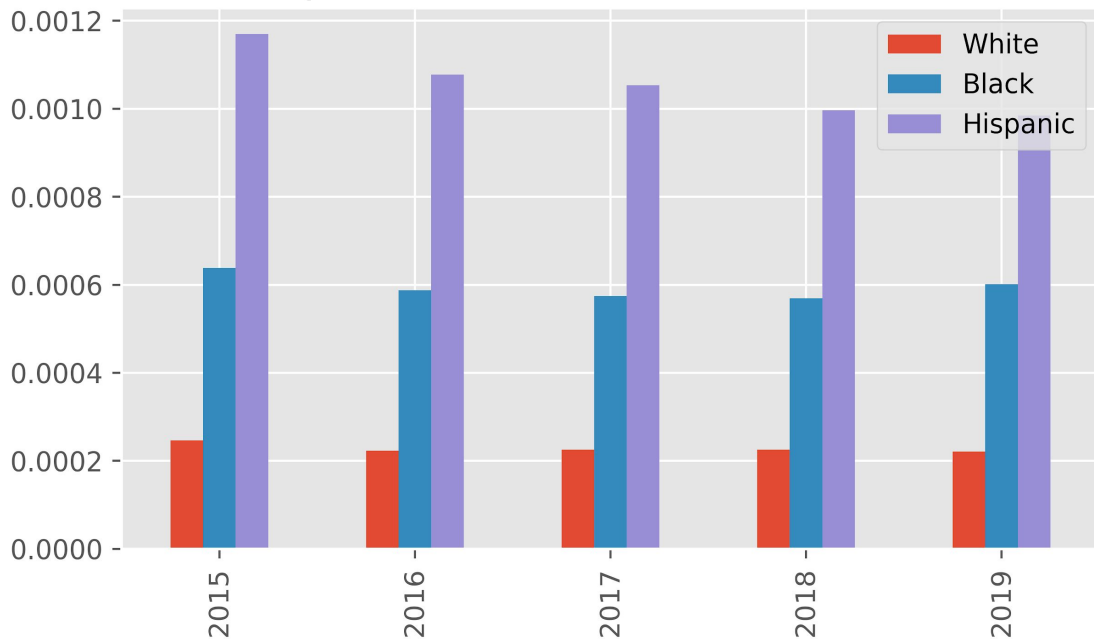


50% are White Americans!

Does this mean  
police are **not**  
racially biased?

# Inspiration for Machine Learning: Does Race Affect How Police Kill?

Proportion of Criminal Offenders Killed



Hispanic people are **4x** more likely to be killed than White people.

Black people are **2.5x** more likely to be killed than White people.

Trend is **consistent** over time

# Predicting the Race of Individuals Killed by Police

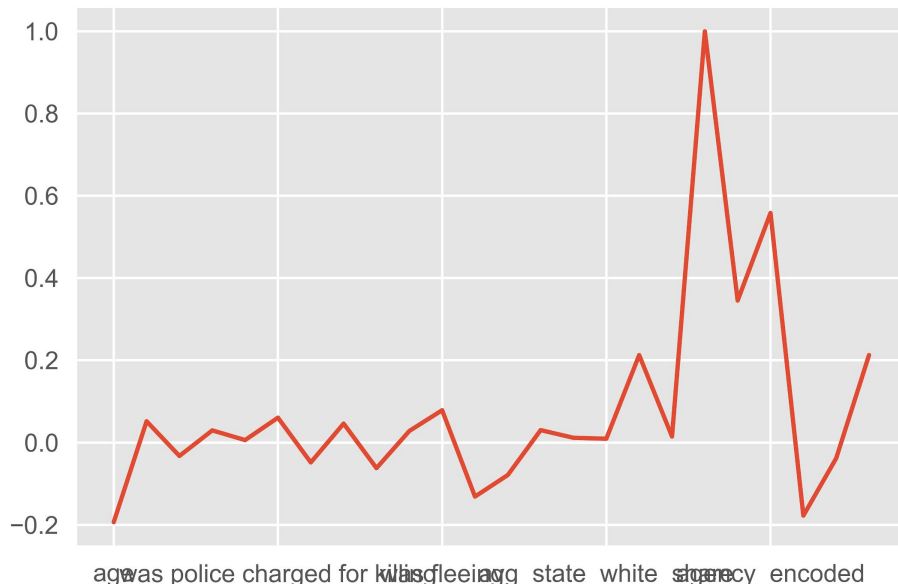
## **Dependent Variable (Y): *Black***

Shows whether an individual is Black (0 or 1)

## **Hypothesis**

Given that an individual was killed by the police, there is sufficient difference in the manner they were killed to differentiate whether they are Black

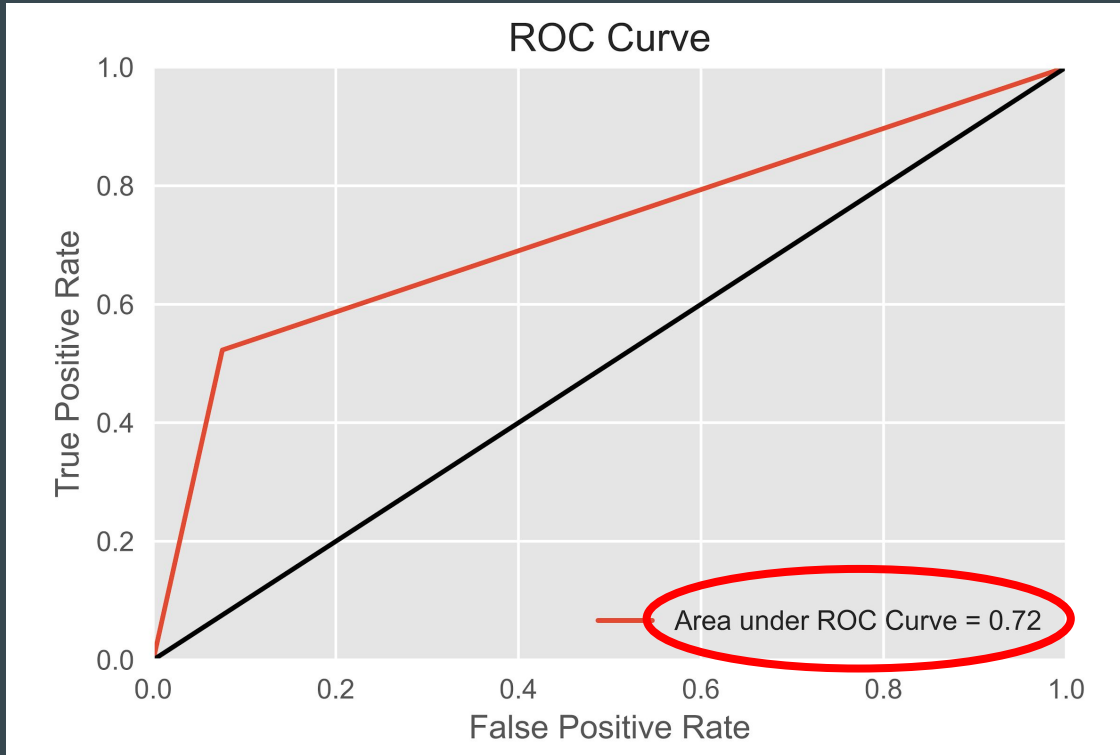
Correlation of Y Variable, "black", With X Variables



# Machine Learning



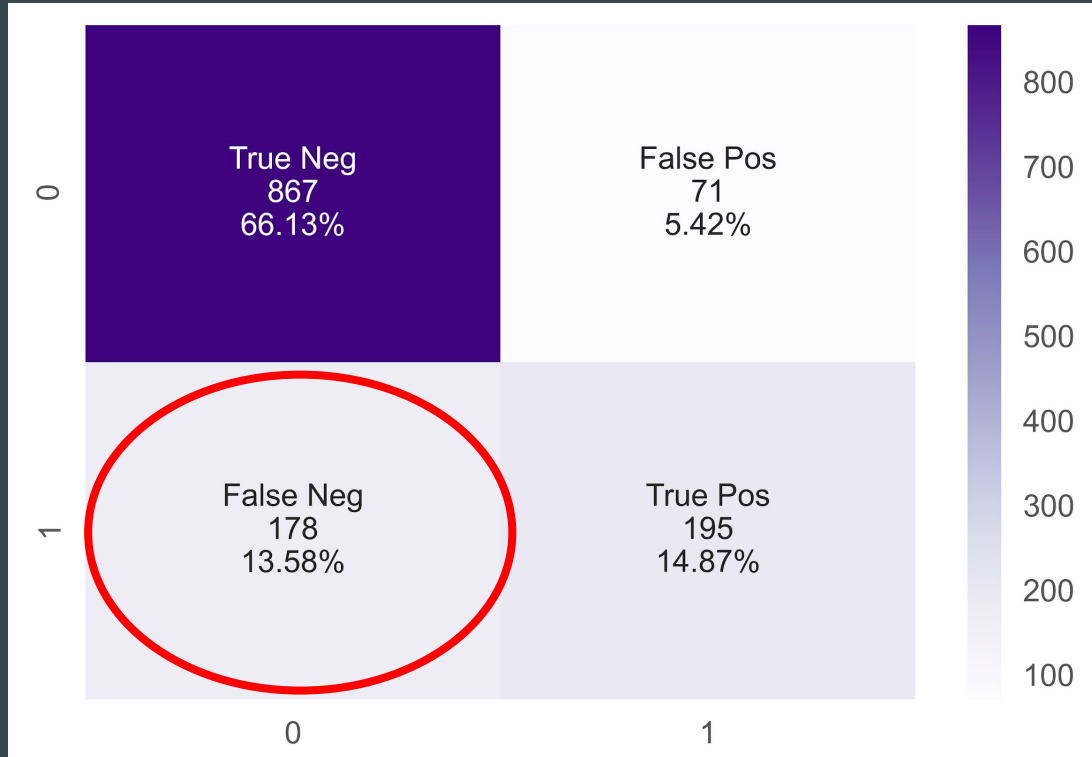
# Predicting the Race of Individuals Killed by Police



**Accuracy Score: 81%**

**Model 1: Logistic Regression**

# Predicting the Race of Individuals Killed by Police



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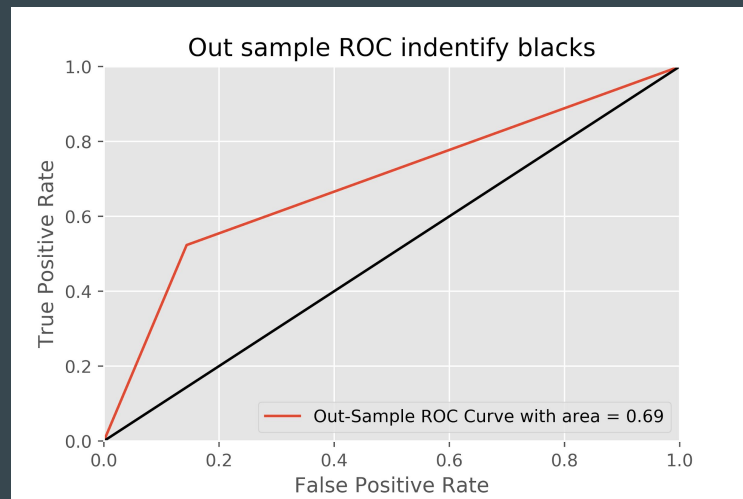
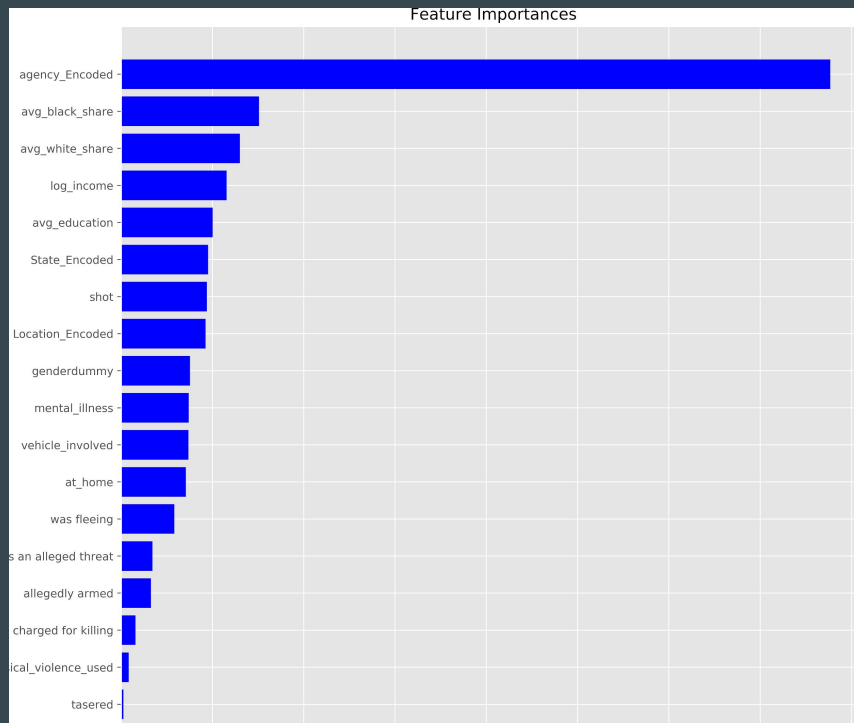
## Advantages of Random Forest Model:

- 1) Does not assume linearity between Y and X variables
- 2) Able to handle missing values:  
Column ***justified*** has over 4000 rows with missing values  
-> We can include it in our Random Forest model but could not in our Logistic Regression model

## Model 2: Random Forest

# Predicting the Race of Individuals Killed by Police

**Accuracy Score: 0.74**

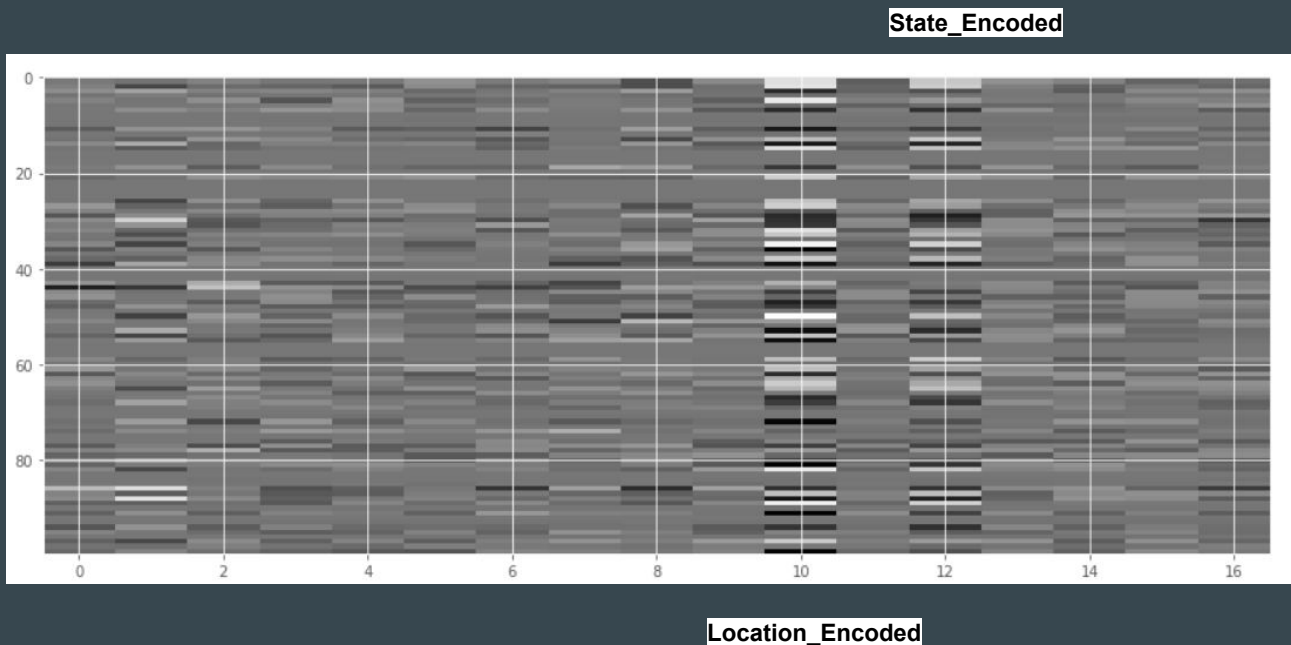


CFM: [825, 126],  
[178, 189]

**Model 2: Random Forest**



# Predicting the Race of Individuals Killed by Police



**Accuracy Score: 0.81**

CFM: [868, 60],  
[260, 130]

**Model 3: Neural Network**