In [ ]:
```
# imports
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

In [ ]:
```
# Load files
edu = pd.read_csv('./education.csv', encoding="ISO-8859-1")
income = pd.read_csv('./income.csv', encoding="ISO-8859-1")
train = pd.read_csv('./police_killings_train.csv', encoding="ISO-8859-1")
test = pd.read_csv('./police_killings_test.csv', encoding="ISO-8859-1")
poverty = pd.read_csv('./poverty.csv', encoding="ISO-8859-1")
race = pd.read_csv('./share_race_by_city.csv', encoding="ISO-8859-1")
```

In [ ]:
```
edu.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29329 entries, 0 to 29328
Data columns (total 3 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   Geographic Area       29329 non-null  object
 1   City                  29329 non-null  object
 2   percent_completed_hs  29329 non-null  object
dtypes: object(3)
memory usage: 687.5+ KB
```

In [ ]:
```
income.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29322 entries, 0 to 29321
Data columns (total 3 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Geographic Area  29322 non-null  object
 1   City             29322 non-null  object
 2   Median Income    29271 non-null  object
dtypes: object(3)
memory usage: 687.4+ KB
```

In [ ]:
```
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2028 entries, 0 to 2027
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       2028 non-null   int64  
 1   name                     2028 non-null   object 
 2   date                     2028 non-null   object 
 3   manner_of_death          2028 non-null   object 
 4   armed                    2022 non-null   object 
 5   age                      1991 non-null   float64
 6   gender                   2028 non-null   object 
 7   race                     1937 non-null   object 
 8   city                     2028 non-null   object 
 9   state                    2028 non-null   object 
 10  signs_of_mental_illness  2028 non-null   bool   
 11  threat_level             2028 non-null   object 
 12  flee                     2001 non-null   object 
 13  body_camera              2028 non-null   bool   
dtypes: bool(2), float64(1), int64(1), object(10)
memory usage: 194.2+ KB
```

In [ ]:
```
test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 507 entries, 0 to 506
Data columns (total 14 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   id                       507 non-null    int64  
 1   name                     507 non-null    object 
 2   date                     507 non-null    object 
 3   manner_of_death          507 non-null    object 
 4   armed                    504 non-null    object 
 5   age                      467 non-null    float64
 6   gender                   507 non-null    object 
 7   race                     403 non-null    object 
 8   city                     507 non-null    object 
 9   state                    507 non-null    object 
 10  signs_of_mental_illness  507 non-null    bool   
 11  threat_level             507 non-null    object 
 12  flee                     469 non-null    object 
 13  body_camera              507 non-null    bool   
dtypes: bool(2), float64(1), int64(1), object(10)
memory usage: 48.6+ KB
```

In [ ]:
```
poverty.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29329 entries, 0 to 29328
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   Geographic Area   29329 non-null  object
 1   City              29329 non-null  object
 2   poverty_rate      29329 non-null  object
dtypes: object(3)
memory usage: 687.5+ KB
```

In [ ]:
```
race.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29268 entries, 0 to 29267
Data columns (total 7 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   Geographic area        29268 non-null  object
 1   City                   29268 non-null  object
 2   share_white            29268 non-null  object
 3   share_black            29268 non-null  object
 4   share_native_american  29268 non-null  object
 5   share_asian            29268 non-null  object
 6   share_hispanic         29268 non-null  object
dtypes: object(7)
memory usage: 1.6+ MB
```

Merge City Data

In [ ]:
```
# column name conformity
race.rename(columns={'Geographic area': 'Geographic Area'},inplace=True)
race.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 29268 entries, 0 to 29267
Data columns (total 7 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   Geographic Area        29268 non-null  object
 1   City                   29268 non-null  object
 2   share_white            29268 non-null  object
 3   share_black            29268 non-null  object
 4   share_native_american  29268 non-null  object
 5   share_asian            29268 non-null  object
 6   share_hispanic         29268 non-null  object
dtypes: object(7)
memory usage: 1.6+ MB
```

In [ ]:

```python
# merge poverty, edu, race, and income based on Geographic Area and City
keys = ['Geographic Area', 'City']
merged = pd.merge(edu, income,on=keys, how='outer')
merged = pd.merge(merged, poverty, on=keys, how='outer')
merged = pd.merge(merged, race, on=keys, how='outer')
merged.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 29477 entries, 0 to 29476
Data columns (total 10 columns):
 #   Column                 Non-Null Count  Dtype 
---  ------                 --------------  ----- 
 0   Geographic Area        29477 non-null  object
 1   City                   29477 non-null  object
 2   percent_completed_hs   29329 non-null  object
 3   Median Income          29271 non-null  object
 4   poverty_rate           29329 non-null  object
 5   share_white            29268 non-null  object
 6   share_black            29268 non-null  object
 7   share_native_american  29268 non-null  object
 8   share_asian            29268 non-null  object
 9   share_hispanic         29268 non-null  object
dtypes: object(10)
memory usage: 2.5+ MB
```

In [ ]:

```python
# rename columns for later work
merged.rename(columns={'Geographic Area': 'state', 'City': 'city'}, inplace=True)
merged
```

Out[ ]:

	state	city	percent_completed_hs	Median Income	poverty_rate	share_white	share_black	share_native_america
0	AL	Abanda CDP	21.2	11207	78.8	67.2	30.2	
1	AL	Abbeville city	69.1	25615	29.1	54.4	41.4	0.
2	AL	Adamsville city	78.9	42575	25.5	52.3	44.9	0.
3	AL	Addison town	81.4	37083	30.7	99.1	0.1	
4	AL	Akron town	68.6	21667	42	13.2	86.5	
...	...	...	...	...	...	...	...	.
29472	WV	Summersville town	NaN	NaN	NaN	97.4	0.4	0.
29473	WV	Upper Falls CDP	NaN	NaN	NaN	96.8	1.1	0.
29474	WI	Delwood CDP	NaN	NaN	NaN	98.6	0.2	0.
29475	WI	Lake Shangrila CDP	NaN	NaN	NaN	95.1	2.2	0.
29476	WI	Pell Lake CDP	NaN	NaN	NaN	94.2	0.3	0.

29477 rows × 10 columns

In [ ]:

```
# convert strings to numeric data and set all non-sense data to null
target = merged.iloc[:,2:10]
for columnName in target:
    merged[columnName] = pd.to_numeric(merged[columnName], errors='coerce')
merged.isnull().sum()
```

Out[ ]:

```
state                      0
city                       0
percent_completed_hs     345
Median Income           2092
poverty_rate             349
share_white              229
share_black              229
share_native_american    229
share_asian              229
share_hispanic           229
dtype: int64
```

In [ ]:

```
numeric_col = merged.columns[2:]
# mean value interpolation: fill missing data with mean value of the state that the data belongs to
merged = merged.fillna(merged.groupby('state')[numeric_col].transform(lambda x: x.fillna(x.mean())))
merged.isnull().sum()
```

Out[ ]:
```
state                     0
city                      0
percent_completed_hs      0
Median Income             0
poverty_rate              0
share_white               0
share_black               0
share_native_american     0
share_asian               0
share_hispanic            0
dtype: int64
```

EDA

Data Cleaning for Victim Data

In [ ]:
```
train.describe()
```

Out[ ]:

	id	age
count	2028.000000	1991.000000
mean	1170.653846	36.580613
std	635.377106	12.886299
min	3.000000	6.000000
25%	633.750000	27.000000
50%	1170.500000	34.000000
75%	1719.250000	45.000000
max	2260.000000	86.000000

In [ ]:
```
train.isnull().sum()
```

Out[ ]:
```
id                          0
name                        0
date                        0
manner_of_death             0
armed                       6
age                        37
gender                      0
race                       91
city                        0
state                       0
signs_of_mental_illness     0
threat_level                0
flee                       27
body_camera                 0
dtype: int64
```

In [ ]:
```
# drop rows with missing armed, race data since filling them with random data may affect our prediction
train.dropna(subset=['armed', 'race'], inplace=True)
train.isnull().sum()
```

Out[ ]:
```
id                         0
name                       0
date                       0
manner_of_death            0
armed                      0
age                       19
gender                     0
race                       0
city                       0
state                      0
signs_of_mental_illness    0
threat_level               0
flee                      21
body_camera                0
dtype: int64
```

In [ ]:
```python
# median imputation for age
train.fillna(value={'age' : train['age'].median()}, inplace=True)
train.isnull().sum()
```

Out[ ]:
```
id                         0
name                       0
date                       0
manner_of_death            0
armed                      0
age                        0
gender                     0
race                       0
city                       0
state                      0
signs_of_mental_illness    0
threat_level               0
flee                      21
body_camera                0
dtype: int64
```

In [ ]:
```python
# fill flee with maximum type of flee
train.fillna(value={'flee' : train['flee'].value_counts().idxmax()}, inplace=True)
train.isnull().sum()
```

Out[ ]:
```
id                         0
name                       0
date                       0
manner_of_death            0
armed                      0
age                        0
gender                     0
race                       0
city                       0
state                      0
signs_of_mental_illness    0
threat_level               0
flee                       0
body_camera                0
dtype: int64
```

In [ ]:
```python
test.describe()
```

Out[ ]:

	id	age
count	507.000000	467.000000
mean	2546.043393	36.710921
std	160.218323	13.643371
min	2261.000000	15.000000
25%	2408.500000	26.000000
50%	2550.000000	34.000000
75%	2682.000000	46.000000
max	2822.000000	91.000000

In [ ]:

```
test.isnull().sum()
```

Out[ ]:

```
id                           0
name                         0
date                         0
manner_of_death              0
armed                        3
age                         40
gender                       0
race                       104
city                         0
state                        0
signs_of_mental_illness      0
threat_level                 0
flee                        38
body_camera                  0
dtype: int64
```

In [ ]:

```
# drop rows with missing race data since filling them with random data may affect our prediction
test.dropna(subset=['race'], inplace=True)
test.isnull().sum()
```

Out[ ]:

```
id                          0
name                        0
date                        0
manner_of_death             0
armed                       1
age                        10
gender                      0
race                        0
city                        0
state                       0
signs_of_mental_illness     0
threat_level                0
flee                       31
body_camera                 0
dtype: int64
```

In [ ]:

```
test.fillna(value={'age' : test['age'].median()}, inplace=True)
test.isnull().sum()
```

Out[ ]:
```
id                         0
name                       0
date                       0
manner_of_death            0
armed                      1
age                        0
gender                     0
race                       0
city                       0
state                      0
signs_of_mental_illness    0
threat_level               0
flee                      31
body_camera                0
dtype: int64
```

In [ ]:
```python
# fill armed with maximum type of armed
test.fillna(value={'armed' : train['armed'].value_counts().idxmax()}, inplace=True)
test.isnull().sum()
```

Out[ ]:
```
id                         0
name                       0
date                       0
manner_of_death            0
armed                      0
age                        0
gender                     0
race                       0
city                       0
state                      0
signs_of_mental_illness    0
threat_level               0
flee                      31
body_camera                0
dtype: int64
```

In [ ]:
```python
# fill flee with maximum type of flee
test.fillna(value={'flee' : train['flee'].value_counts().idxmax()}, inplace=True)
test.isnull().sum()
```

Out[ ]:
```
id                         0
name                       0
date                       0
manner_of_death            0
armed                      0
age                        0
gender                     0
race                       0
city                       0
state                      0
signs_of_mental_illness    0
threat_level               0
flee                       0
body_camera                0
dtype: int64
```

Dangerous level

> To evaluate the dangerous level of states/cities, we need more data about state/city population. We obtain the data from US census in files `nst-est2017-popchg2010_2017` and `sub-est2017_all.csv`

> We also obtain file `states.csv` for [state name, abbreviation] mapping.

In [ ]:
```python
state_names = pd.read_csv("./states.csv", encoding="ISO-8859-1")
state_names.head()
```

Out[ ]:

	State	Abbreviation
0	Alabama	AL
1	Alaska	AK
2	Arizona	AZ
3	Arkansas	AR
4	California	CA

In [ ]:

```
read_state_pop = pd.read_csv('./nst-est2017-popchg2010_2017.csv', encoding='ISO-8859-1')
read_state_pop.head()
```

Out[ ]:

	SUMLEV	REGION	DIVISION	STATE	NAME	ESTIMATESBASE2010	POPESTIMATE2010	POPESTIMATE2011	POPES
0	10	0	0	0	United States	308758105	309338421	311644280	
1	20	1	0	0	Northeast Region	55318350	55388349	55642659	
2	20	2	0	0	Midwest Region	66929794	66973360	67141501	
3	20	3	0	0	South Region	114563024	114869241	116060993	
4	20	4	0	0	West Region	71946937	72107471	72799127	

5 rows × 55 columns

In [ ]:

```
state_abbre = pd.DataFrame({'state': state_names['State'], 'abbre': state_names['Abbreviation']})
mapping = state_abbre.set_index('state').to_dict('dict')['abbre']
state_pop = read_state_pop.rename(columns={'NAME': 'state', 'POPESTIMATE2017': 'population'}).loc[5:55, ['sta
state_pop.insert(0, 'abbre', state_pop['state'])
state_pop['abbre'].replace(mapping, inplace=True)
state_pop.head()
```

Out[ ]:

	abbre	state	population
5	AL	Alabama	4874747
6	AK	Alaska	739795
7	AZ	Arizona	7016270
8	AR	Arkansas	3004279
9	CA	California	39536653

In [ ]:

```
counts = train['state'].value_counts().reset_index().rename({'state': 'victims', 'index':'abbre'}, axis=1)

merged_state_stat = pd.merge(state_pop, counts, on='abbre', how='outer')

merged_state_stat.describe()
```

Out[ ]:

	population	victims
count	5.100000e+01	51.000000
mean	6.386651e+06	37.882353
std	7.316763e+06	50.366913
min	5.793150e+05	2.000000
25%	1.766400e+06	10.000000
50%	4.454189e+06	28.000000
75%	7.211006e+06	41.500000
max	3.953665e+07	318.000000

State level

In [ ]:

```
# filter outliers
merged_state_stat = merged_state_stat.loc[merged_state_stat['victims'] > 20]

victim_density_col = "victim per million population"
merged_state_stat[victim_density_col] = merged_state_stat['victims']/merged_state_stat['population']*1_000_00

merged_state_stat

# 10 most dangerous states
merged_state_stat.sort_values(victim_density_col, ascending=False).head(10)
```

Out[ ]:

	abbre	state	population	victims	victim per million population
31	NM	New Mexico	2088070	41	19.635357
36	OK	Oklahoma	3930864	54	13.737438
2	AZ	Arizona	7016270	88	12.542277
28	NV	Nevada	2998039	31	10.340092
5	CO	Colorado	5607154	56	9.987241
18	LA	Louisiana	4684333	46	9.819968
0	AL	Alabama	4874747	41	8.410693
4	CA	California	39536653	318	8.043169
17	KY	Kentucky	4454189	35	7.857772
25	MO	Missouri	6113532	45	7.360720

> To obtain the 10 most dangerous states, we use filtered victim density in each state to reduce the impact of low victim numbers on states with low populations. The results are New Mexico, Oklahoma, Arizona, Nevada, Colorado, Louisiana, Alabama, California, Kentucky, and Missouri. Notice that New Mexico has the most fatal police killing, which is nearly double of the 6th (Louisiana).

City level

In [ ]:

```
city_data = pd.read_csv("./sub-est2017_all.csv", encoding="ISO-8859-1")
city_data.head()
```

Out[ ]:

	SUMLEV	STATE	COUNTY	PLACE	COUSUB	CONCIT	PRIMGEO_FLAG	FUNCSTAT	NAME	STNAME	CENSUS201
0	40	1	0	0	0	0	0	A	Alabama	Alabama	47
1	162	1	0	124	0	0	0	A	Abbeville city	Alabama	
2	162	1	0	460	0	0	0	A	Adamsville city	Alabama	
3	162	1	0	484	0	0	0	A	Addison town	Alabama	
4	162	1	0	676	0	0	0	A	Akron town	Alabama	

In [ ]:

```
city_pop = city_data.rename({'NAME': 'city', 'STNAME': 'state', 'POPESTIMATE2017': 'population'}, axis=1)[['s
city_pop.head()
```

Out[ ]:

	state	city	population
0	Alabama	Alabama	4874747
1	Alabama	Abbeville city	2567
2	Alabama	Adamsville city	4347
3	Alabama	Addison town	728
4	Alabama	Akron town	332

In [ ]:

```
city_victims = train[['state','city']].value_counts().reset_index().rename({0: 'victims'}, axis=1)

abbre_to_state = state_abbre.set_index('abbre').to_dict('dict')['state']

city_victims.replace({'state': abbre_to_state}, inplace=True)

city_victims
```

Out[ ]:

	state	city	victims
0	California	Los Angeles	31
1	Arizona	Phoenix	22
2	Texas	Houston	22
3	Illinois	Chicago	21
4	Nevada	Las Vegas	15
...	...	...	...
1211	Indiana	Harmony	1
1212	Indiana	Kokomo	1
1213	Indiana	Monon	1
1214	Indiana	Shelbyville	1
1215	Wyoming	Laramie	1

1216 rows × 3 columns

In [ ]:

```
merged_city_stat = pd.merge(city_pop, city_victims, on=['state','city'], how='inner')

merged_city_stat
```

Out[ ]:

	state	city	population	victims
0	Alabama	Lawrence County	33049	1
1	Alabama	Macon County	18755	1
2	Alabama	Washington County	16531	1
3	Arizona	La Paz County	20601	1
4	California	Kings County	150101	1
5	California	San Diego County	3337685	1
6	California	Siskiyou County	43853	1
7	Colorado	Park County	17905	1
8	Florida	Orange County	1348975	1
9	Georgia	Cobb County	755754	1
10	Georgia	Paulding County	159445	1
11	Georgia	Whitfield County	104658	1
12	Idaho	Jefferson County	28446	1
13	Kentucky	Daviess County	100374	1
14	Louisiana	Evangeline Parish	33708	1
15	Louisiana	Livingston Parish	138228	1
16	Louisiana	Ouachita Parish	155874	1
17	Michigan	Berrien County	154259	1
18	Missouri	Franklin County	103330	1
19	Nevada	Carson City	54745	2
20	Nevada	Carson City	54745	2
21	Nevada	Carson City	54745	2
22	New York	New York	19849399	8
23	North Carolina	Anson County	24991	1
24	North Carolina	Ashe County	26957	1
25	North Carolina	Gaston County	220182	1
26	North Carolina	Iredell County	175711	1
27	Oklahoma	Coal County	5642	1
28	Oklahoma	Okmulgee County	38930	1
29	Oklahoma	Pottawatomie County	72226	1
30	Oregon	Clackamas County	412672	1
31	Oregon	Josephine County	86352	1
32	Pennsylvania	Huntingdon County	45491	1
33	Pennsylvania	York County	446078	1
34	South Carolina	Chesterfield County	45948	1
35	Tennessee	Decatur County	11751	1
36	Tennessee	Gibson County	49111	1
37	Texas	Bexar County	1958578	1

	state	city	population	victims
38	Texas	Ellis County	173620	2
39	Texas	Henderson County	81064	1
40	Texas	Leon County	17243	1
41	Texas	Wood County	44314	1
42	Virginia	Grayson County	15665	1
43	Virginia	Powhatan County	28601	1
44	Virginia	Scott County	21865	1
45	Virginia	York County	67739	1
46	Washington	Thurston County	280588	1
47	West Virginia	Braxton County	14237	1

> NOTE: After merge, only 48 rows remaining: city population data is insufficient to match with city victim data, therefore, here we choose to compare the absolute victim number in the 10 most dangerous states.

In [ ]:

```
city_matched = city_victims[city_victims['state'].isin(['New Mexico', 'Oklahoma', 'Arizona', 'Nevada','Colora
city_matched.sort_values('victims', ascending=False).head(10)
```

Out[ ]:

	state	city	victims
0	California	Los Angeles	31
1	Arizona	Phoenix	22
4	Nevada	Las Vegas	15
10	Arizona	Tucson	12
11	Oklahoma	Oklahoma City	11
12	California	Bakersfield	11
13	New Mexico	Albuquerque	11
18	California	Long Beach	9
20	California	San Bernardino	9
16	California	San Francisco	9

> Because of insufficient city population data, we roughly use subsets of states with absolute victims to rate the dangerous level at city level. The results are Los Angeles, Phoenix, Las Vegas, Tucson, Oklahoma City, Bakersfield, Albuquerque, Long Beach, San Bernardino, San Francisco.

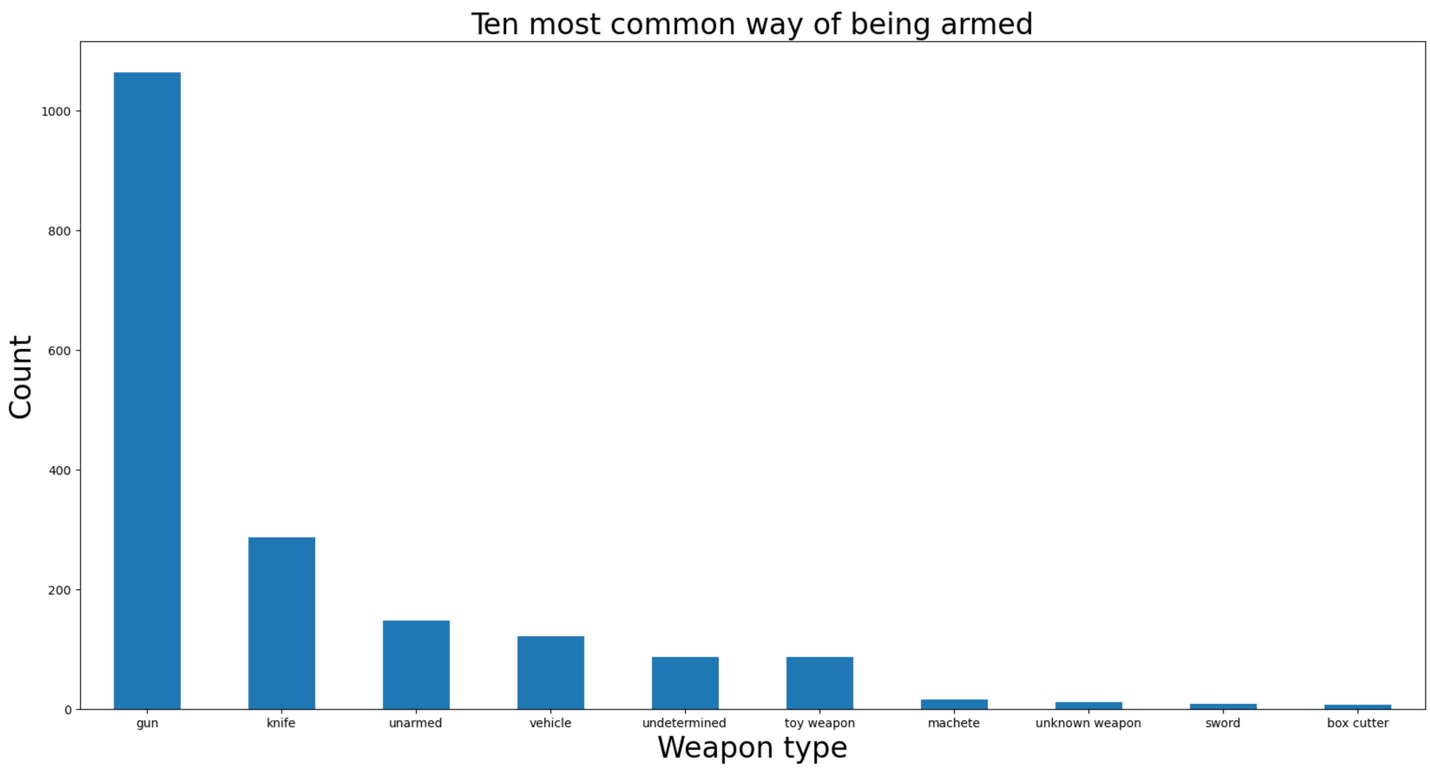
Armed

In [ ]:

```
# 10 most common way of being armed
train.value_counts(["armed"]).head(10)
```

```
Out[ ]: armed
gun                1063
knife               286
unarmed             148
vehicle             121
undetermined         86
toy weapon           86
machete              15
unknown weapon       11
sword                 8
box cutter            7
dtype: int64
```

```
In [ ]: # plot the bar graph
plt.figure(figsize=(20,10))
ax = train.value_counts("armed").head(10).plot(kind='bar', rot=0)
ax.set_xlabel("Weapon type", fontsize = 24)
ax.set_ylabel("Count", fontsize = 24)
ax.set_title('Ten most common way of being armed', fontsize = 24)
plt.show()
```



> The bar graph of weapon types shows a nice shape of power distribution curve, from which we can see that gun is the most common way of being armed.

Age Distribution

By all races

```
In [ ]: # 10 most listed ages of the victims
train.value_counts(["age"]).head(10)
```

Out[ ]:

```
age
25.0    76
36.0    75
34.0    75
31.0    74
29.0    73
30.0    61
24.0    60
23.0    59
28.0    58
26.0    57
dtype: int64
```

The ten most listed ages of all victims range between 20 and 35. The following histogram displays age distribution of all victims.

In [ ]:

```
train['age'].describe()
```

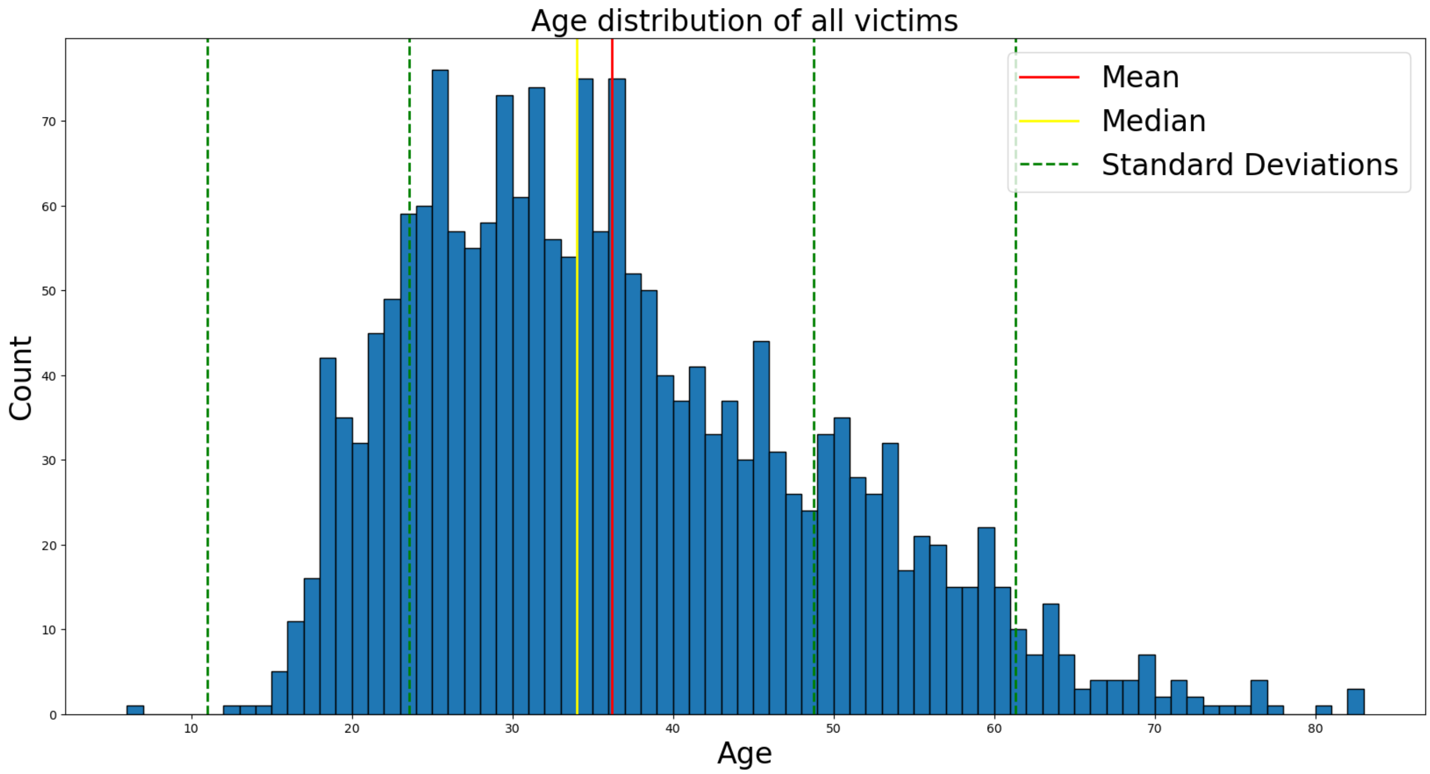
Out[ ]:

```
count    1932.000000
mean       36.166149
std        12.590792
min         6.000000
25%        26.000000
50%        34.000000
75%        44.250000
max        83.000000
Name: age, dtype: float64
```

In [ ]:

```
# age distribution of all victims
plt.figure(figsize=(20,10))
plt.hist(train['age'], bins=np.arange(min(train['age']), max(train['age']+1), 1),edgecolor='black')

plt.xlabel('Age', fontsize=24)
plt.ylabel('Count',fontsize=24)
plt.title('Age distribution of all victims', fontsize=24)
# more information
mean = train['age'].mean()
plt.axvline(mean, color='red', linewidth=2, label='Mean')
median = train['age'].median()
plt.axvline(median, color='yellow', linewidth=2, label='Median')
std = train['age'].std()
stdn2 = mean - 2*std
stdn1 = mean - std
stdp1 = mean + std
stdp2 = mean + 2*std
plt.axvline(stdn2, color='green', linewidth=2, label='Standard Deviations', linestyle='--')
plt.axvline(stdn1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp2, color='green', linewidth=2, linestyle='--')
plt.legend(fontsize=24)
plt.show()
```



In [ ]:
```python
# skewness
skew = 3*(mean - median)/std
skew
```

Out[ ]:
```
0.5161269480395437
```

> The age distribution of all races is moderately skewed right with skewness of 0.52. The median of ages of all victims is about 34, whereas the mean value is about 36. As a result, the distribution is positive skewed. The standard deviation is about 13. Within one standard deviation (13) from the mean, the age ranges between 24 to 49.

Specific Race

In [ ]:
```python
# recorded race types
train['race'].unique()
```

Out[ ]:
```
array(['A', 'W', 'H', 'B', 'O', 'N'], dtype=object)
```

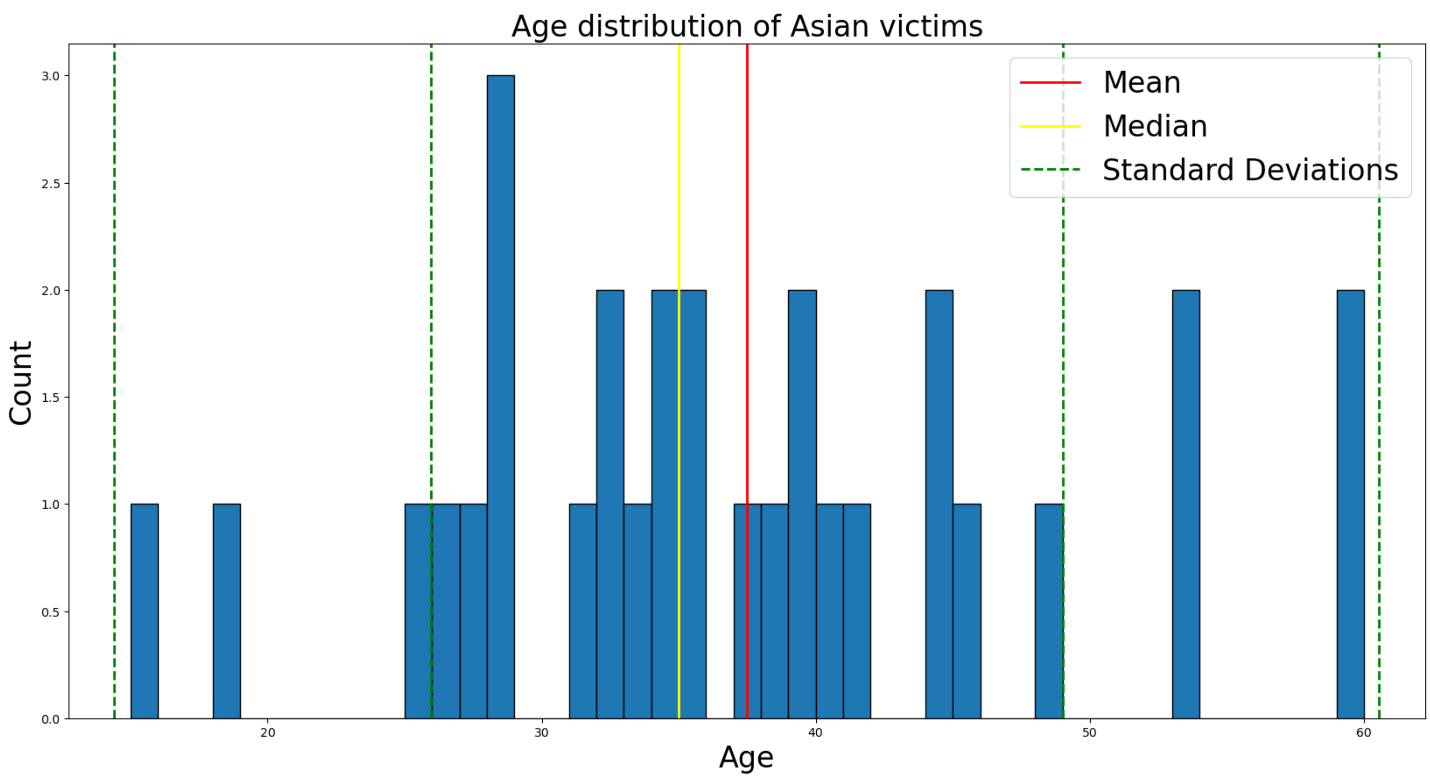
Race A (Asian)

In [ ]:
```python
race = train[train['race']=='A']
race['age'].describe()
```

Out[ ]:
```
count    31.000000
mean     37.483871
std      11.535080
min      15.000000
25%      29.500000
50%      35.000000
75%      44.000000
max      61.000000
Name: age, dtype: float64
```

In [ ]:
```python
# age distribution of Asian victims
plt.figure(figsize=(20,10))
plt.hist(race['age'], bins=np.arange(min(race['age']), max(race['age']), 1),edgecolor='black')
```

```
plt.xlabel('Age', fontsize=24)
plt.ylabel('Count',fontsize=24)
plt.title('Age distribution of Asian victims', fontsize=24)
# more information
mean = race['age'].mean()
plt.axvline(mean, color='red', linewidth=2, label='Mean')
median = race['age'].median()
plt.axvline(median, color='yellow', linewidth=2, label='Median')
std = race['age'].std()
stdn2 = mean - 2*std
stdn1 = mean - std
stdp1 = mean + std
stdp2 = mean + 2*std
plt.axvline(stdn2, color='green', linewidth=2, label='Standard Deviations', linestyle='--')
plt.axvline(stdn1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp2, color='green', linewidth=2, linestyle='--')
plt.legend(fontsize=24)
plt.show()
```



In [ ]:
```
# skewness
skew = 3*(mean - median)/std
skew
```

Out[ ]: 0.040323891927275445

> The ages of Asian victims are loosely distributed between 15 and 60, and it is moderately skewed right with a skewness of 0.65. The mean value is about 37 and is slightly greater than the median age 35. Within one standard deviation (12) from the mean, the majority data range between 26 to 49.

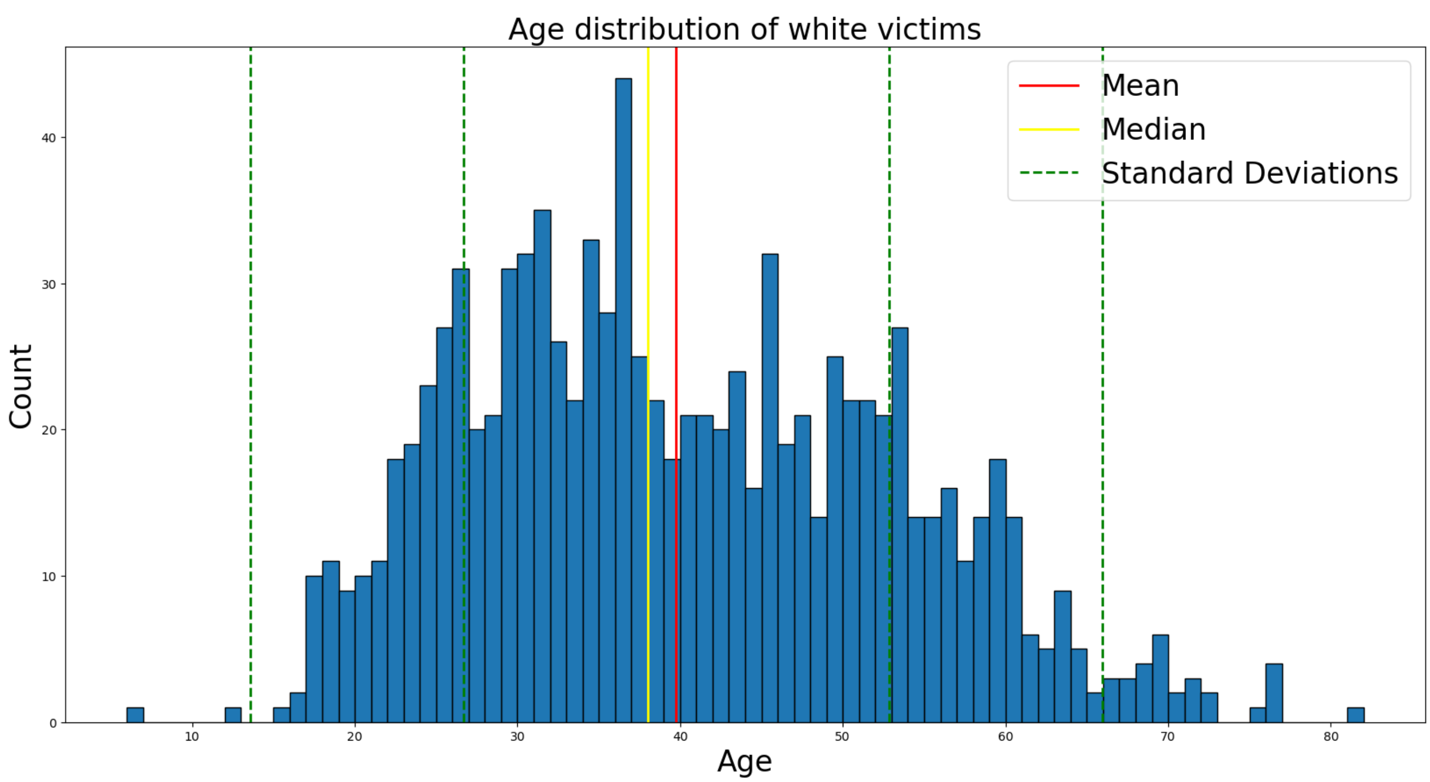
Race W (White)

In [ ]:
```
race = train[train['race']=='W']
race['age'].describe()
```

```
Out[ ]: count    995.000000
        mean      39.763819
        std       13.102578
        min        6.000000
        25%       30.000000
        50%       38.000000
        75%       50.000000
        max       83.000000
        Name: age, dtype: float64
```

```
In [ ]: # age distribution of white victims
plt.figure(figsize=(20,10))
plt.hist(race['age'], bins=np.arange(min(race['age']), max(race['age']), 1),edgecolor='black')

plt.xlabel('Age', fontsize=24)
plt.ylabel('Count',fontsize=24)
plt.title('Age distribution of white victims', fontsize=24)
# more information
mean = race['age'].mean()
plt.axvline(mean, color='red', linewidth=2, label='Mean')
median = race['age'].median()
plt.axvline(median, color='yellow', linewidth=2, label='Median')
std = race['age'].std()
stdn2 = mean - 2*std
stdn1 = mean - std
stdp1 = mean + std
stdp2 = mean + 2*std
plt.axvline(stdn2, color='green', linewidth=2, label='Standard Deviations', linestyle='--')
plt.axvline(stdn1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp2, color='green', linewidth=2, linestyle='--')
plt.legend(fontsize=24)
plt.show()
```




```
In [ ]: # skewness
skew = 3*(mean - median)/std
skew
```

```
Out[ ]: 0.40384854735971853
```

> The age distribution of white victims is approximately symmetric with a skewness of 0.40. The mean is 40, which is slightly greater the median 38. Within one standard deviation (13) from the mean, the ages range between 27 and 53.

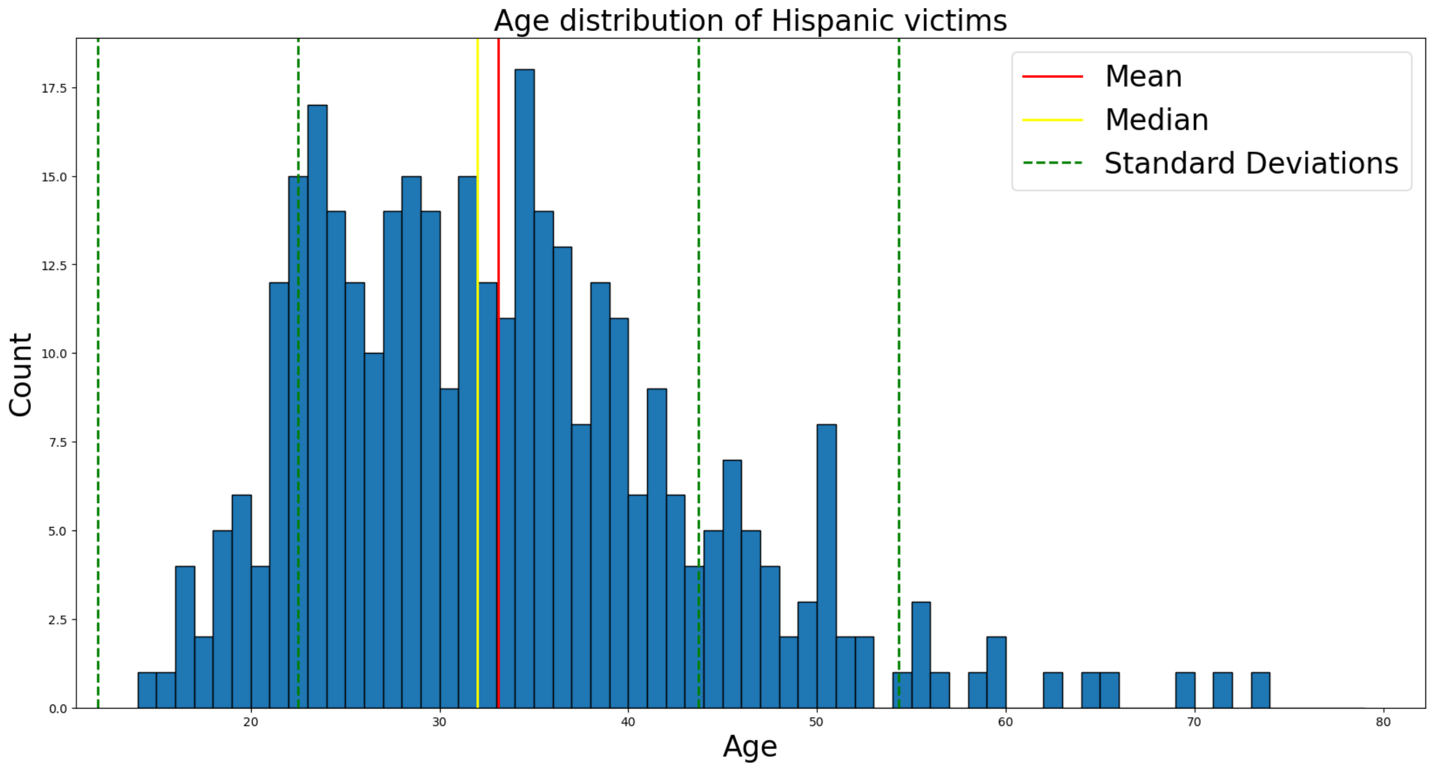
Race H (Hispanic)

In [ ]:
```
race = train[train['race']=='H']
race['age'].describe()
```

Out[ ]:
```
count    347.000000
mean      33.103746
std       10.603776
min       14.000000
25%       25.000000
50%       32.000000
75%       39.000000
max       80.000000
Name: age, dtype: float64
```

In [ ]:
```
# age distribution of Hispanic victims
plt.figure(figsize=(20,10))
plt.hist(race['age'], bins=np.arange(min(race['age']), max(race['age']), 1),edgecolor='black')

plt.xlabel('Age', fontsize=24)
plt.ylabel('Count',fontsize=24)
plt.title('Age distribution of Hispanic victims', fontsize=24)
# more information
mean = race['age'].mean()
plt.axvline(mean, color='red', linewidth=2, label='Mean')
median = race['age'].median()
plt.axvline(median, color='yellow', linewidth=2, label='Median')
std = race['age'].std()
stdn2 = mean - 2*std
stdn1 = mean - std
stdp1 = mean + std
stdp2 = mean + 2*std
plt.axvline(stdn2, color='green', linewidth=2, label='Standard Deviations', linestyle='--')
plt.axvline(stdn1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp2, color='green', linewidth=2, linestyle='--')
plt.legend(fontsize=24)
plt.show()
```




```
In [ ]: # skewness
        skew = 3*(mean - median)/std
        skew
```

```
Out[ ]: 0.3122698072361164
```

> The age distribution of hispanic victims is shaped like a normal distribution. The mean is 33 and is slightly greater the median 32, which results in a skewness of 0.31. Within one standard deviation (11) from the mean, the ages range between 22 and 43.

Race B (Black)

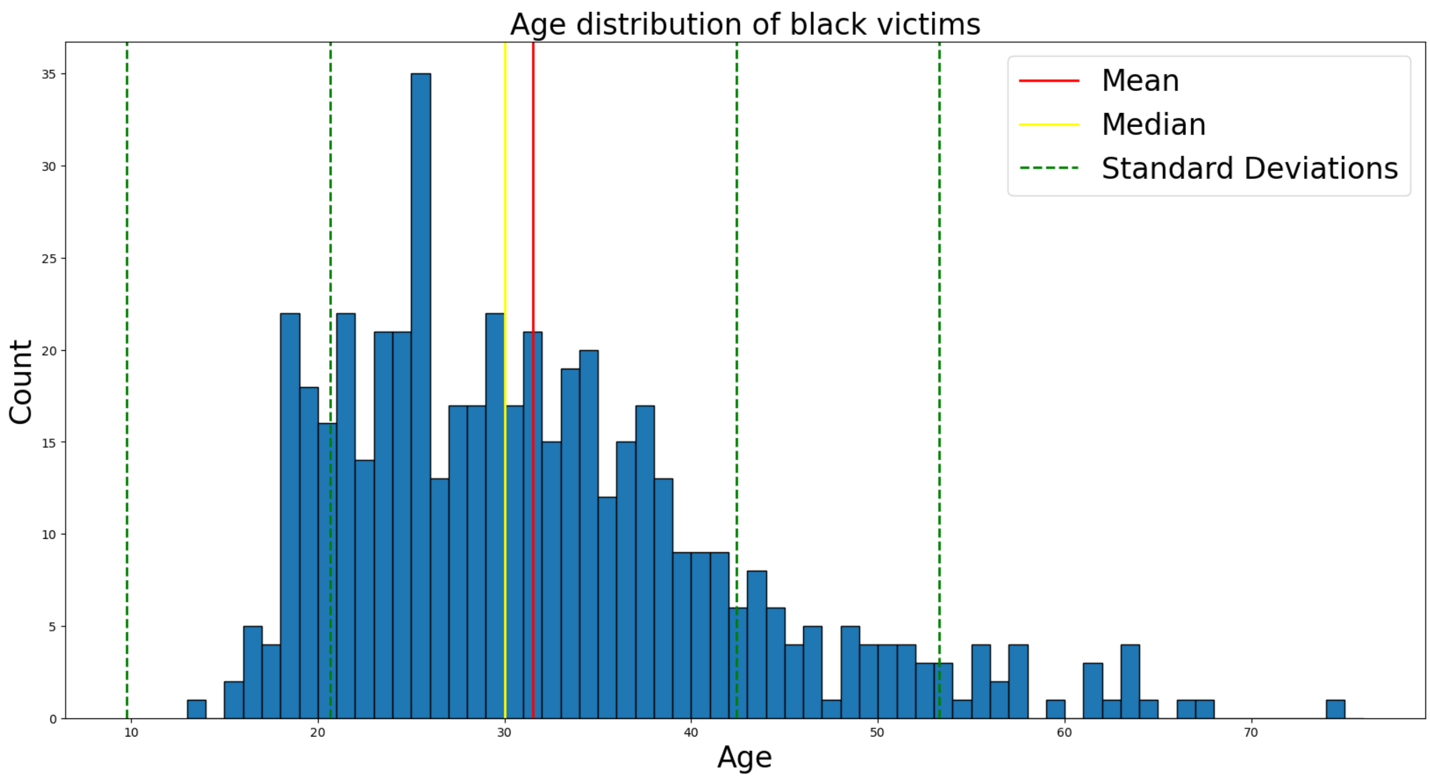
```
In [ ]: race = train[train['race']=='B']
        race['age'].describe()
```

```
Out[ ]: count    504.000000
        mean      31.533730
        std       10.874435
        min       13.000000
        25%       24.000000
        50%       30.000000
        75%       37.000000
        max       77.000000
        Name: age, dtype: float64
```

```
In [ ]: # age distribution of black victims
        plt.figure(figsize=(20,10))
        plt.hist(race['age'], bins=np.arange(min(race['age']), max(race['age']), 1),edgecolor='black')

        plt.xlabel('Age', fontsize=24)
        plt.ylabel('Count',fontsize=24)
        plt.title('Age distribution of black victims', fontsize=24)
        # more information
        mean = race['age'].mean()
        plt.axvline(mean, color='red', linewidth=2, label='Mean')
        median = race['age'].median()
        plt.axvline(median, color='yellow', linewidth=2, label='Median')
        std = race['age'].std()
        stdn2 = mean - 2*std
```

```
stdn1 = mean - std
stdp1 = mean + std
stdp2 = mean + 2*std
plt.axvline(stdn2, color='green', linewidth=2, label='Standard Deviations', linestyle='--')
plt.axvline(stdn1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp2, color='green', linewidth=2, linestyle='--')
plt.legend(fontsize=24)
plt.show()
```



In [ ]:
```
# skewness
skew = 3*(mean - median)/std
skew
```

Out[ ]:
```
0.4231199636775382
```

> The age distribution of black victims has a moderate positive skewness (0.42). The mean is 32 and is slightly greater the median 30. Within one standard deviation (11) from the mean, the ages range between 20 and 42.

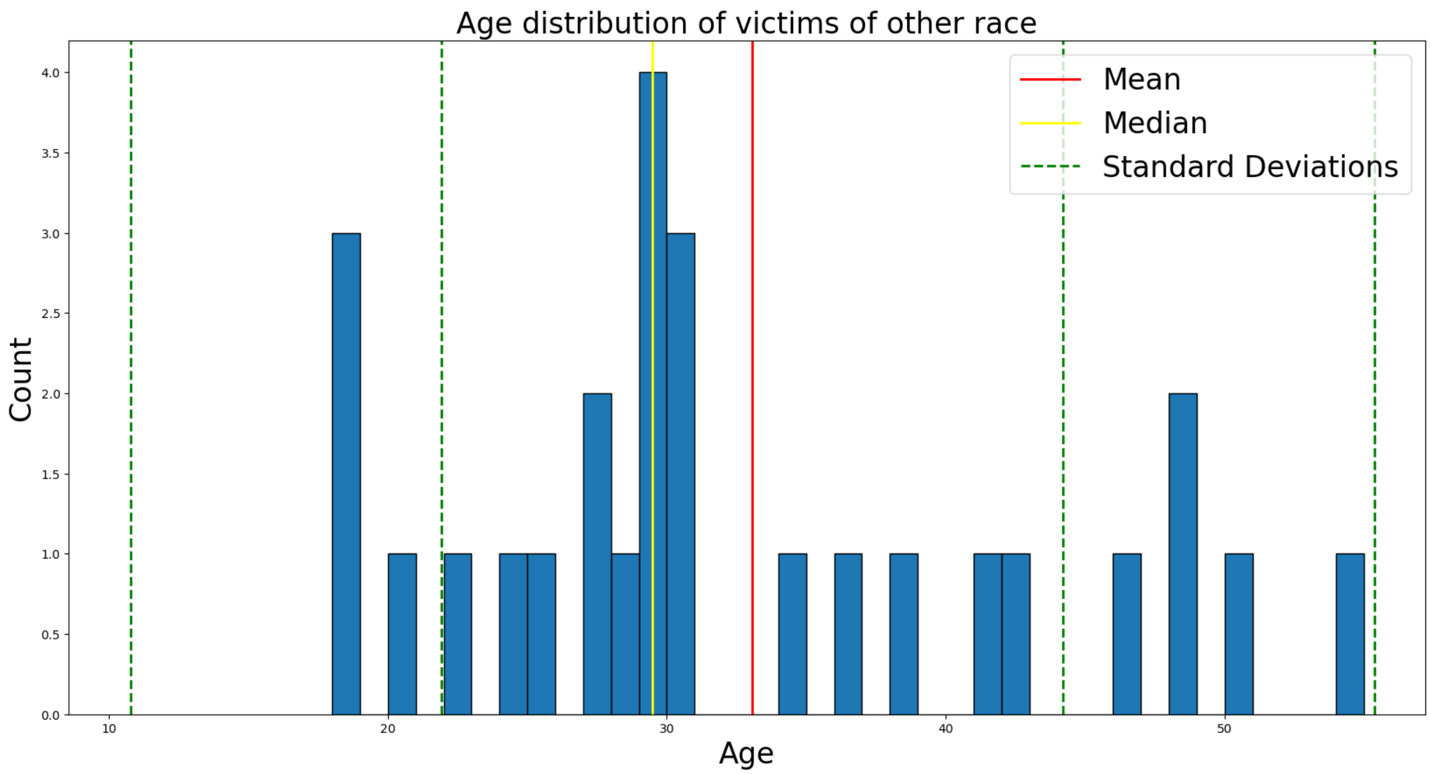
Race O (Other)

In [ ]:
```
race = train[train['race']=='O']
race['age'].describe()
```

Out[ ]:
```
count    28.000000
mean     33.071429
std      11.148588
min      18.000000
25%      26.500000
50%      29.500000
75%      41.250000
max      56.000000
Name: age, dtype: float64
```

In [ ]:
```
# age distribution of victims of other race
plt.figure(figsize=(20,10))
plt.hist(race['age'], bins=np.arange(min(race['age']), max(race['age']), 1),edgecolor='black')
```

```
plt.xlabel('Age', fontsize=24)
plt.ylabel('Count',fontsize=24)
plt.title('Age distribution of victims of other race', fontsize=24)
# more information
mean = race['age'].mean()
plt.axvline(mean, color='red', linewidth=2, label='Mean')
median = race['age'].median()
plt.axvline(median, color='yellow', linewidth=2, label='Median')
std = race['age'].std()
stdn2 = mean - 2*std
stdn1 = mean - std
stdp1 = mean + std
stdp2 = mean + 2*std
plt.axvline(stdn2, color='green', linewidth=2, label='Standard Deviations', linestyle='--')
plt.axvline(stdn1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp2, color='green', linewidth=2, linestyle='--')
plt.legend(fontsize=24)
plt.show()
```



In [ ]:
```
# skewness
skew = 3*(mean - median)/std
skew
```

Out[ ]:
```
0.9610442243114937
```

> The ages of victims with other races are loosely distributed with a skewness of 0.96. The mean is 33 and is slightly greater the median 29, which results in a skewness of 0.3. Within one standard deviation (11) from the mean, the ages range between 23 and 44.

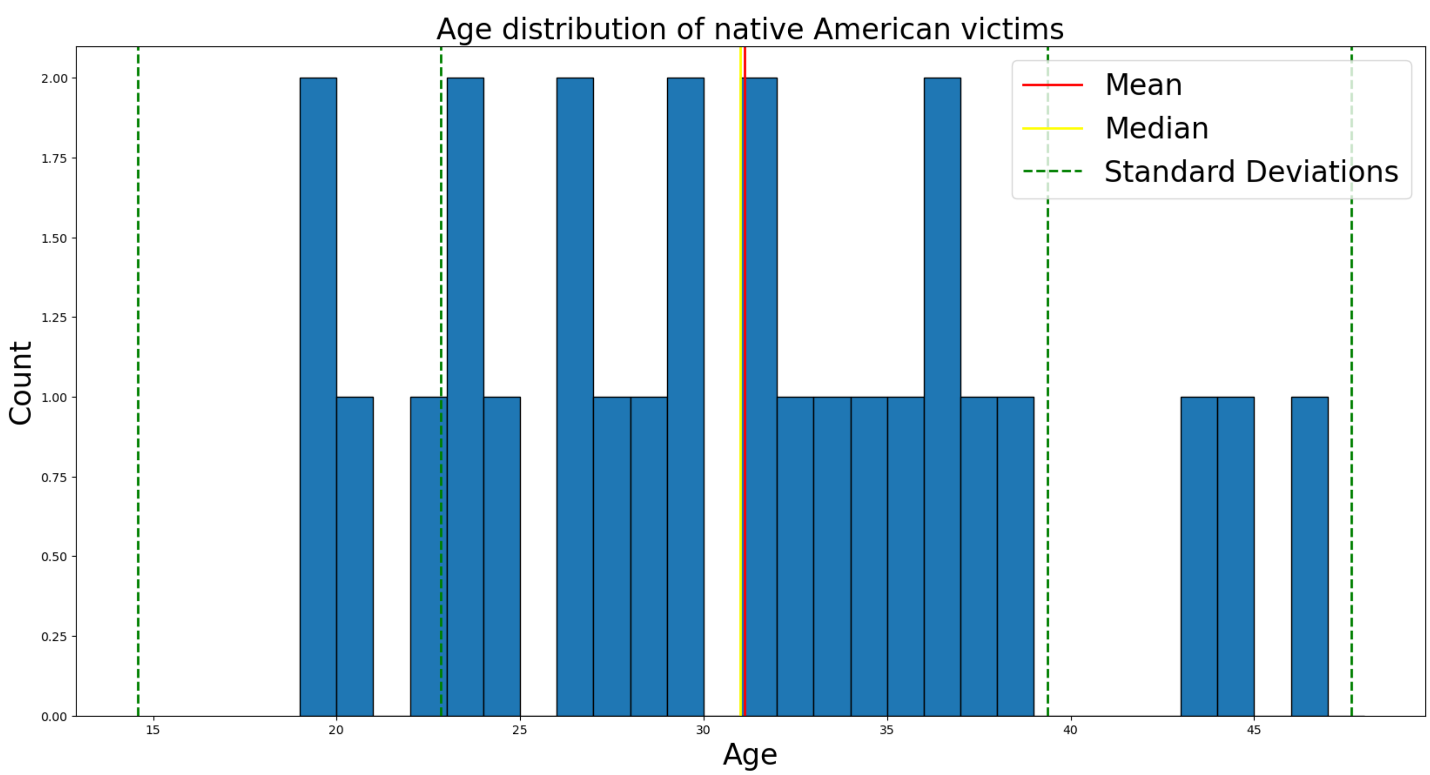
Race N (Native American)

In [ ]:
```
race = train[train['race']=='N']
race['age'].describe()
```

Out[ ]:
```
count    27.000000
mean     31.111111
std       8.266398
min      19.000000
25%      25.000000
50%      31.000000
75%      36.000000
max      49.000000
Name: age, dtype: float64
```

In [ ]:
```
# age distribution of native American victims
plt.figure(figsize=(20,10))
plt.hist(race['age'], bins=np.arange(min(race['age']), max(race['age']), 1),edgecolor='black')

plt.xlabel('Age', fontsize=24)
plt.ylabel('Count',fontsize=24)
plt.title('Age distribution of native American victims', fontsize=24)
# more information
mean = race['age'].mean()
plt.axvline(mean, color='red', linewidth=2, label='Mean')
median = race['age'].median()
plt.axvline(median, color='yellow', linewidth=2, label='Median')
std = race['age'].std()
stdn2 = mean - 2*std
stdn1 = mean - std
stdp1 = mean + std
stdp2 = mean + 2*std
plt.axvline(stdn2, color='green', linewidth=2, label='Standard Deviations', linestyle='--')
plt.axvline(stdn1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp1, color='green', linewidth=2, linestyle='--')
plt.axvline(stdp2, color='green', linewidth=2, linestyle='--')
plt.legend(fontsize=24)
plt.show()
```



In [ ]:
```
# skewness
skew = 3*(mean - median)/std
skew
```

Out[ ]: 0.040323891927275445

> The age distribution of native American victims is almost symmetric with a skewness of 0.04. The mean and median are aout 31. Within one standard deviation (8) from the mean, the ages range between 23 and 39.

Total number of people killed per race

In [ ]:
```
# total number of people killed per race
train.value_counts(["race"])
```

Out[ ]:
```
race
W       995
B       504
H       347
A        31
O        28
N        27
dtype: int64
```

Race ratio

In [ ]:
```
# number of people killed in each race / total number of people killed in all races
killed_ratio=train['race'].value_counts(normalize=True) * 100
killed_ratio
```

Out[ ]:
```
W    51.501035
B    26.086957
H    17.960663
A     1.604555
O     1.449275
N     1.397516
Name: race, dtype: float64
```

> More than half of the victims are white people, more than a quarter are black people, and the number of hispanic victims is about 1/5 of the total. The remaining races (Asian, Other, Native Americans) accounted for less than 5 percent of the victims.

Number of people killed per race as a proportion of respective races

According to the estimated race proportion in the U.S. from 2010 through 2019 by U.S. Census Bureau:

- White: 60.1%
- Hispanic: 18.8%
- Black: 13.4%
- Asian: 5.9%
- Native Americans: 1.3%
- Other (two or more races): 2.8%

Also, the American population from 2014 to 2017 increases from 320 million to 330 million.

In [ ]:
```
# here, we take the median 325 million as the population constant
p = 325
# white population in millions
wp = 0.601 * p
# hispanic population in millions
hp = 0.188 * p
# black population in millions
bp = 0.134 * p
# Asian population in millions
ap = 0.059 * p
```

```python
# native American population in millions
np = 0.013 * p
# other race population in millions
op = 0.028 * p
r = ['W', 'B', 'H', 'A', 'O', 'N']
n = train.value_counts('race').tolist()
t = [wp,bp,hp,ap,op,np]
population = pd.DataFrame({'race': r, 'number of killed': n, 'population in millions': t})
population
```

Out[ ]:

	race	number of killed	population in millions
0	W	995	195.325
1	B	504	43.550
2	H	347	61.100
3	A	31	19.175
4	O	28	9.100
5	N	27	4.225

In [ ]:

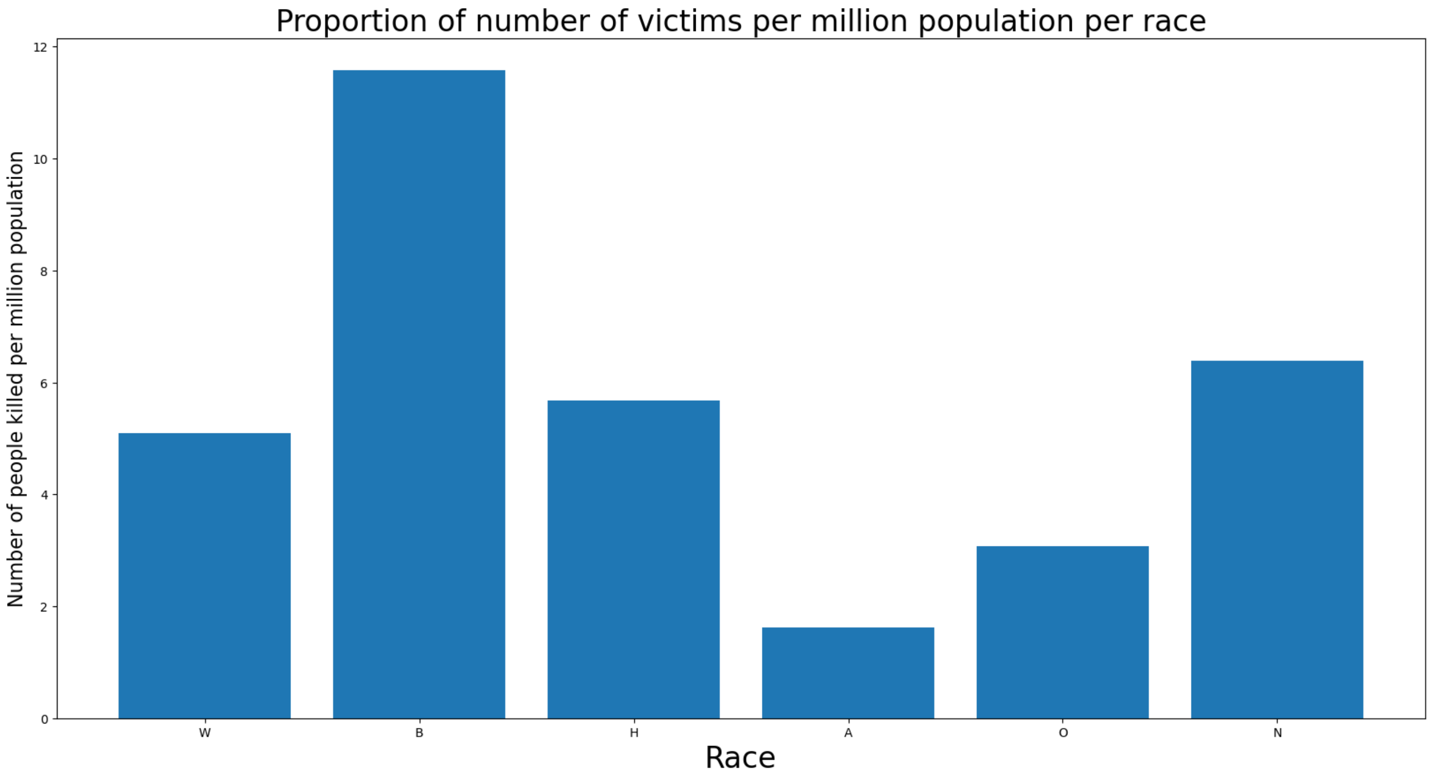
```python
# now, we can calculate the proportion of number of victims in respective race population
proportion = pd.DataFrame({'race': r, 'number of people killed per million': population['number of killed']/p
proportion
```

Out[ ]:

	race	number of people killed per million
0	W	5.094074
1	B	11.572905
2	H	5.679214
3	A	1.616688
4	O	3.076923
5	N	6.390533

In [ ]:

```python
# plot the bar graph
plt.figure(figsize=(20,10))
plt.bar(x=proportion['race'], height=proportion['number of people killed per million'])
plt.xlabel("Race", fontsize = 24)
plt.ylabel("Number of people killed per million population", fontsize = 16)
plt.title('Proportion of number of victims per million population per race', fontsize = 24)
plt.show()
```



> From the proportion data and the bar graph we can see that
>
> - the number of black victims is twice as much as white victims in a scale of per million population of each race
> - the number of native American victims is slightly higher than the number of hispanic victims which is slightly higher than the number of white victims per million population
> - the number of victims with other races (two or more races) is about half of the number of white victims per million population
> - the proportion of number of Asian victims per million population has the least value

Machine Learning algorithm

In [ ]:

```
# imports
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score, accuracy_score, precision_recall_fscore_support
```

Data Modified

In [ ]:

```
train
```

Out[ ]:

	id	name	date	manner_of_death	armed	age	gender	race	city	state	signs_of_mental_illnes
0	3	Tim Elliot	02/01/15	shot	gun	53.0	M	A	Shelton	WA	Tru
1	4	Lewis Lee Lembke	02/01/15	shot	gun	47.0	M	W	Aloha	OR	Fals
2	5	John Paul Quintero	03/01/15	shot and Tasered	unarmed	23.0	M	H	Wichita	KS	Fals
3	8	Matthew Hoffman	04/01/15	shot	toy weapon	32.0	M	W	San Francisco	CA	Tru
4	9	Michael Rodriguez	04/01/15	shot	nail gun	39.0	M	H	Evans	CO	Fals
...	...	...	...	...	...	...	...	...	...	...	.
2023	2256	Jeremy Lopez-Robledo	24/01/17	shot	knife	29.0	M	H	Las Cruces	NM	Tru
2024	2257	Jonathan David Sper	24/01/17	shot	unarmed	30.0	M	W	Algoma Township	MI	Tru
2025	2258	Jose Efrain Rodriguez	24/01/17	shot and Tasered	gun	18.0	M	H	Lancaster City	PA	Fals
2026	2259	Ramon Milanez	24/01/17	shot	gun	32.0	M	H	Kuna	ID	Fals
2027	2260	Micah R. Lambert	25/01/17	shot	vehicle	37.0	M	W	Oxford	AL	Tru

1932 rows × 14 columns

In [ ]:

```
merged
```

Out[ ]:

	state	city	percent_completed_hs	Median Income	poverty_rate	share_white	share_black	share_native_am
0	AL	Abanda CDP	21.200000	11207.000000	78.800000	67.2	30.2	
1	AL	Abbeville city	69.100000	25615.000000	29.100000	54.4	41.4	
2	AL	Adamsville city	78.900000	42575.000000	25.500000	52.3	44.9	
3	AL	Addison town	81.400000	37083.000000	30.700000	99.1	0.1	
4	AL	Akron town	68.600000	21667.000000	42.000000	13.2	86.5	
...	...	...	...	...	...	...	...	
29472	WV	Summersville town	82.345050	39097.117318	21.134406	97.4	0.4	
29473	WV	Upper Falls CDP	82.345050	39097.117318	21.134406	96.8	1.1	
29474	WI	Delwood CDP	90.263964	50411.400778	12.858687	98.6	0.2	
29475	WI	Lake Shangrila CDP	90.263964	50411.400778	12.858687	95.1	2.2	
29476	WI	Pell Lake CDP	90.263964	50411.400778	12.858687	94.2	0.3	

29477 rows × 10 columns

city names do not match; for exmaple,

- train `[ 'city' ]` = 'New York', merged `[ 'city' ]` = 'New York City'
- train `[ 'city' ]` = 'Oregon City', merged `[ 'city' ]` = 'Oregon City city'

In [ ]:

```
# delete the last word in merged['city'] for city name conformity
merged.city=merged.city.apply(lambda x: ' '.join(x.split()[:-1]))
merged
```

Out[ ]:

	state	city	percent_completed_hs	Median Income	poverty_rate	share_white	share_black	share_native_am
0	AL	Abanda	21.200000	11207.000000	78.800000	67.2	30.2	
1	AL	Abbeville	69.100000	25615.000000	29.100000	54.4	41.4	
2	AL	Adamsville	78.900000	42575.000000	25.500000	52.3	44.9	
3	AL	Addison	81.400000	37083.000000	30.700000	99.1	0.1	
4	AL	Akron	68.600000	21667.000000	42.000000	13.2	86.5	
...	...	...	...	...	...	...	...	
29472	WV	Summersville	82.345050	39097.117318	21.134406	97.4	0.4	
29473	WV	Upper Falls	82.345050	39097.117318	21.134406	96.8	1.1	
29474	WI	Delwood	90.263964	50411.400778	12.858687	98.6	0.2	
29475	WI	Lake Shangrila	90.263964	50411.400778	12.858687	95.1	2.2	
29476	WI	Pell Lake	90.263964	50411.400778	12.858687	94.2	0.3	

29477 rows × 10 columns

In [ ]:
```
train
```

Out[ ]:

	id	name	date	manner_of_death	armed	age	gender	race	city	state	signs_of_mental_illnes
0	3	Tim Elliot	02/01/15	shot	gun	53.0	M	A	Shelton	WA	Tru
1	4	Lewis Lee Lembke	02/01/15	shot	gun	47.0	M	W	Aloha	OR	Fals
2	5	John Paul Quintero	03/01/15	shot and Tasered	unarmed	23.0	M	H	Wichita	KS	Fals
3	8	Matthew Hoffman	04/01/15	shot	toy weapon	32.0	M	W	San Francisco	CA	Tru
4	9	Michael Rodriguez	04/01/15	shot	nail gun	39.0	M	H	Evans	CO	Fals
...	...	...	...	...	...	...	...	...	...	...	.
2023	2256	Jeremy Lopez-Robledo	24/01/17	shot	knife	29.0	M	H	Las Cruces	NM	Tru
2024	2257	Jonathan David Sper	24/01/17	shot	unarmed	30.0	M	W	Algoma Township	MI	Tru
2025	2258	Jose Efrain Rodriguez	24/01/17	shot and Tasered	gun	18.0	M	H	Lancaster City	PA	Fals
2026	2259	Ramon Milanez	24/01/17	shot	gun	32.0	M	H	Kuna	ID	Fals
2027	2260	Micah R. Lambert	25/01/17	shot	vehicle	37.0	M	W	Oxford	AL	Tru

1932 rows × 14 columns

In [ ]:

```python
# drop unnecessary columns
train = train.drop(['id','name','date','armed'],axis=1)
train
```

Out[ ]:

	manner_of_death	age	gender	race	city	state	signs_of_mental_illness	threat_level	flee	body_camera
0	shot	53.0	M	A	Shelton	WA	True	attack	Not fleeing	False
1	shot	47.0	M	W	Aloha	OR	False	attack	Not fleeing	False
2	shot and Tasered	23.0	M	H	Wichita	KS	False	other	Not fleeing	False
3	shot	32.0	M	W	San Francisco	CA	True	attack	Not fleeing	False
4	shot	39.0	M	H	Evans	CO	False	attack	Not fleeing	False
...	...	...	...	...	...	...	...	...	...	...
2023	shot	29.0	M	H	Las Cruces	NM	True	attack	Foot	True
2024	shot	30.0	M	W	Algoma Township	MI	True	attack	Not fleeing	False
2025	shot and Tasered	18.0	M	H	Lancaster City	PA	False	attack	Not fleeing	False
2026	shot	32.0	M	H	Kuna	ID	False	attack	Car	False
2027	shot	37.0	M	W	Oxford	AL	True	attack	Car	False

1932 rows × 10 columns

In [ ]:

```python
# drop unnecessary columns
test = test.drop(['id','name','date','armed'],axis=1)
test
```

Out[ ]:

	manner_of_death	age	gender	race	city	state	signs_of_mental_illness	threat_level	flee	body_camera
0	shot	54.0	M	B	Southaven	MS	False	attack	Not fleeing	False
1	shot	50.0	M	W	Millston	WI	True	attack	Not fleeing	True
2	shot	28.0	M	H	Charlotte	NC	False	other	Car	False
3	shot	59.0	M	W	Overlea	MD	True	attack	Not fleeing	True
4	shot	24.0	M	B	Atlanta	GA	False	other	Car	True
...	...	...	...	...	...	...	...	...	...	...
495	shot	25.0	M	B	Dayton	OH	False	attack	Car	False
497	shot	39.0	M	B	Homer	LA	False	attack	Car	False
500	shot	34.0	M	H	Chowchilla	CA	False	attack	Not fleeing	False
505	shot	28.0	M	B	Oshkosh	WI	False	attack	Car	True
506	shot	32.0	M	B	Brooklyn	NY	True	attack	Not fleeing	False

403 rows × 10 columns

Label Encoding

In [ ]:

```
# import encoder
from sklearn import preprocessing
# race encode
race_map = preprocessing.LabelEncoder()
train['race'] = race_map.fit_transform(train['race'])
train['race']
```

Out[ ]:

```
0       0
1       5
2       2
3       5
4       2
       ..
2023    2
2024    5
2025    2
2026    2
2027    5
Name: race, Length: 1932, dtype: int32
```

In [ ]:

```
test['race'] = race_map.transform(test['race'])
test['race']
```

Out[ ]:
```
0      1
1      5
2      2
3      5
4      1
      ..
495    1
497    1
500    2
505    1
506    1
Name: race, Length: 403, dtype: int32
```

In [ ]:
```
# manner_of_death encode
death_map = preprocessing.LabelEncoder()
train['manner_of_death'] = death_map.fit_transform(train['manner_of_death'])
train['manner_of_death']
```

Out[ ]:
```
0       0
1       0
2       1
3       0
4       0
       ..
2023    0
2024    0
2025    1
2026    0
2027    0
Name: manner_of_death, Length: 1932, dtype: int32
```

In [ ]:
```
test['manner_of_death'] = death_map.transform(test['manner_of_death'])
test['manner_of_death']
```

Out[ ]:
```
0      0
1      0
2      0
3      0
4      0
      ..
495    0
497    0
500    0
505    0
506    0
Name: manner_of_death, Length: 403, dtype: int32
```

In [ ]:
```
# gender encode
gender_map = preprocessing.LabelEncoder()
train['gender'] = gender_map.fit_transform(train['gender'])
train['gender']
```

Out[ ]:
```
0       1
1       1
2       1
3       1
4       1
       ..
2023    1
2024    1
2025    1
2026    1
2027    1
Name: gender, Length: 1932, dtype: int32
```

In [ ]:
```
test['gender'] = gender_map.transform(test['gender'])
test['gender']
```

```
Out[ ]: 0      1
        1      1
        2      1
        3      1
        4      1
              ..
        495    1
        497    1
        500    1
        505    1
        506    1
        Name: gender, Length: 403, dtype: int32
```

```
In [ ]: # signs_of_mental_illness encode
        signs_of_mental_illness_map = preprocessing.LabelEncoder()
        train['signs_of_mental_illness'] = signs_of_mental_illness_map.fit_transform(train['signs_of_mental_illness']
        train['signs_of_mental_illness']
```

```
Out[ ]: 0       1
        1       0
        2       0
        3       1
        4       0
               ..
        2023    1
        2024    1
        2025    0
        2026    0
        2027    1
        Name: signs_of_mental_illness, Length: 1932, dtype: int64
```

```
In [ ]: test['signs_of_mental_illness'] = signs_of_mental_illness_map.transform(test['signs_of_mental_illness'])
        test['signs_of_mental_illness']
```

```
Out[ ]: 0      0
        1      1
        2      0
        3      1
        4      0
              ..
        495    0
        497    0
        500    0
        505    0
        506    1
        Name: signs_of_mental_illness, Length: 403, dtype: int64
```

```
In [ ]: # threat_level encode
        threat_level_map = preprocessing.LabelEncoder()
        train['threat_level'] = threat_level_map.fit_transform(train['threat_level'])
        train['threat_level']
```

```
Out[ ]: 0       0
        1       0
        2       1
        3       0
        4       0
               ..
        2023    0
        2024    0
        2025    0
        2026    0
        2027    0
        Name: threat_level, Length: 1932, dtype: int32
```

```
In [ ]: test['threat_level'] = threat_level_map.transform(test['threat_level'])
        test['threat_level']
```

Out[ ]:
```
0      0
1      0
2      1
3      0
4      1
      ..
495    0
497    0
500    0
505    0
506    0
Name: threat_level, Length: 403, dtype: int32
```

In [ ]:
```
# flee encode
flee_map = preprocessing.LabelEncoder()
train['flee'] = flee_map.fit_transform(train['flee'])
train['flee']
```

Out[ ]:
```
0       2
1       2
2       2
3       2
4       2
       ..
2023    1
2024    2
2025    2
2026    0
2027    0
Name: flee, Length: 1932, dtype: int32
```

In [ ]:
```
test['flee'] = flee_map.transform(test['flee'])
test['flee']
```

Out[ ]:
```
0      2
1      2
2      0
3      2
4      0
      ..
495    0
497    0
500    2
505    0
506    2
Name: flee, Length: 403, dtype: int32
```

In [ ]:
```
# body_camera encode
body_camera_map = preprocessing.LabelEncoder()
train['body_camera'] = body_camera_map.fit_transform(train['body_camera'])
train['body_camera']
```

Out[ ]:
```
0       0
1       0
2       0
3       0
4       0
       ..
2023    1
2024    0
2025    0
2026    0
2027    0
Name: body_camera, Length: 1932, dtype: int64
```

In [ ]:
```
test['body_camera'] = body_camera_map.transform(test['body_camera'])
test['body_camera']
```

```
Out[ ]: 0      0
        1      1
        2      0
        3      1
        4      1
              ..
        495    0
        497    0
        500    0
        505    1
        506    0
        Name: body_camera, Length: 403, dtype: int64
```

Merge City Data and Victim Data

Balancing Victim Data

```
In [ ]: train.race.value_counts()
```

```
Out[ ]: 5    995
        1    504
        2    347
        0     31
        4     28
        3     27
        Name: race, dtype: int64
```

```
In [ ]: from sklearn.utils import resample
        # split into majority and minorities
        minor0 = train[train.race==0]
        minor1 = train[train.race==1]
        minor2 = train[train.race==2]
        minor3 = train[train.race==3]
        minor4 = train[train.race==4]
        major = train[train.race==5]

        # Upsample minority classes
        minor0_up = resample(minor0, replace=True, n_samples=major.race.value_counts().tolist()[0], random_state=100)
        minor1_up = resample(minor1, replace=True, n_samples=major.race.value_counts().tolist()[0], random_state=100)
        minor2_up = resample(minor2, replace=True, n_samples=major.race.value_counts().tolist()[0], random_state=100)
        minor3_up = resample(minor3, replace=True, n_samples=major.race.value_counts().tolist()[0], random_state=100)
        minor4_up = resample(minor4, replace=True, n_samples=major.race.value_counts().tolist()[0], random_state=100)
        # combine
        train = pd.concat([minor0_up,minor1_up,minor2_up,minor3_up,minor4_up,major])
        # display new counts
        train.race.value_counts()
```

```
Out[ ]: 0    995
        1    995
        2    995
        3    995
        4    995
        5    995
        Name: race, dtype: int64
```

```
In [ ]: # merge City Data and Victim Data
        train_merge = pd.merge(train,merged, on=['state','city'], how = 'outer', indicator=True)
        train_merge
```

Out[ ]:

	manner_of_death	age	gender	race	city	state	signs_of_mental_illness	threat_level	flee	body_camera
0	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
1	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
2	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
3	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
4	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
...	...	...	...	...	...	...	...	...	...	...
34460	NaN	NaN	NaN	NaN	Riverton	WA	NaN	NaN	NaN	NaN
34461	NaN	NaN	NaN	NaN	Upper Falls	WV	NaN	NaN	NaN	NaN
34462	NaN	NaN	NaN	NaN	Delwood	WI	NaN	NaN	NaN	NaN
34463	NaN	NaN	NaN	NaN	Lake Shangrila	WI	NaN	NaN	NaN	NaN
34464	NaN	NaN	NaN	NaN	Pell Lake	WI	NaN	NaN	NaN	NaN

34465 rows × 19 columns

In [ ]:

```
# keep rows with full Victim Data
train_merge = train_merge[train_merge['_merge'].isin(['both','left_only'])].drop('_merge', axis=1)
train_merge
```

Out[ ]:

	manner_of_death	age	gender	race	city	state	signs_of_mental_illness	threat_level	flee	body_camera
0	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
1	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
2	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
3	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
4	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
...	...	...	...	...	...	...	...	...	...	...
5971	0.0	57.0	1.0	5.0	Waldoboro	ME	0.0	0.0	2.0	0.0
5972	0.0	52.0	1.0	5.0	Brooklet	GA	0.0	0.0	1.0	0.0
5973	0.0	27.0	1.0	5.0	Springfield	IL	1.0	0.0	2.0	1.0
5974	0.0	30.0	1.0	5.0	Algoma Township	MI	1.0	0.0	2.0	0.0
5975	0.0	37.0	1.0	5.0	Oxford	AL	1.0	0.0	0.0	0.0

5976 rows × 18 columns

In [ ]:

```
# median imputation for missing City Data
train_merge = train_merge.fillna(train_merge.median(numeric_only=True))
train_merge
```

Out[ ]:

	manner_of_death	age	gender	race	city	state	signs_of_mental_illness	threat_level	flee	body_camera
0	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
1	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
2	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
3	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
4	0.0	59.0	1.0	0.0	El Monte	CA	0.0	0.0	2.0	0.0
...	...	...	...	...	...	...	...	...	...	...
5971	0.0	57.0	1.0	5.0	Waldoboro	ME	0.0	0.0	2.0	0.0
5972	0.0	52.0	1.0	5.0	Brooklet	GA	0.0	0.0	1.0	0.0
5973	0.0	27.0	1.0	5.0	Springfield	IL	1.0	0.0	2.0	1.0
5974	0.0	30.0	1.0	5.0	Algoma Township	MI	1.0	0.0	2.0	0.0
5975	0.0	37.0	1.0	5.0	Oxford	AL	1.0	0.0	0.0	0.0

5976 rows × 18 columns

In [ ]:

```
train_merge.isnull().sum()
```

Out[ ]:

```
manner_of_death            0
age                        0
gender                     0
race                       0
city                       0
state                      0
signs_of_mental_illness    0
threat_level               0
flee                       0
body_camera                0
percent_completed_hs       0
Median Income              0
poverty_rate               0
share_white                0
share_black                0
share_native_american      0
share_asian                0
share_hispanic             0
dtype: int64
```

In [ ]:

```
# merge City Data and Victim Data for testing set
test_merge = pd.merge(test,merged, on=['state','city'], how = 'outer', indicator=True)
test_merge
```

Out[ ]:

	manner_of_death	age	gender	race	city	state	signs_of_mental_illness	threat_level	flee	body_camera
0	0.0	54.0	1.0	1.0	Southaven	MS	0.0	0.0	2.0	0.0
1	0.0	41.0	1.0	2.0	Southaven	MS	0.0	0.0	2.0	0.0
2	0.0	50.0	1.0	5.0	Millston	WI	1.0	0.0	2.0	1.0
3	0.0	28.0	1.0	2.0	Charlotte	NC	0.0	1.0	0.0	0.0
4	0.0	25.0	1.0	5.0	Charlotte	NC	1.0	1.0	2.0	0.0
...	...	...	...	...	...	...	...	...	...	...
29589	NaN	NaN	NaN	NaN	Riverton	WA	NaN	NaN	NaN	NaN
29590	NaN	NaN	NaN	NaN	Upper Falls	WV	NaN	NaN	NaN	NaN
29591	NaN	NaN	NaN	NaN	Delwood	WI	NaN	NaN	NaN	NaN
29592	NaN	NaN	NaN	NaN	Lake Shangrila	WI	NaN	NaN	NaN	NaN
29593	NaN	NaN	NaN	NaN	Pell Lake	WI	NaN	NaN	NaN	NaN

29594 rows × 19 columns

In [ ]:

```python
# keep rows with full Victim Data
test_merge = test_merge[test_merge['_merge'].isin(['both','left_only'])].drop('_merge', axis=1)
test_merge
```

Out[ ]:

	manner_of_death	age	gender	race	city	state	signs_of_mental_illness	threat_level	flee	body_camera	p
0	0.0	54.0	1.0	1.0	Southaven	MS	0.0	0.0	2.0	0.0	
1	0.0	41.0	1.0	2.0	Southaven	MS	0.0	0.0	2.0	0.0	
2	0.0	50.0	1.0	5.0	Millston	WI	1.0	0.0	2.0	1.0	
3	0.0	28.0	1.0	2.0	Charlotte	NC	0.0	1.0	0.0	0.0	
4	0.0	25.0	1.0	5.0	Charlotte	NC	1.0	1.0	2.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	
398	0.0	16.0	1.0	1.0	Marion	AR	0.0	2.0	2.0	0.0	
399	0.0	25.0	1.0	1.0	Dayton	OH	0.0	0.0	0.0	0.0	
400	0.0	39.0	1.0	1.0	Homer	LA	0.0	0.0	0.0	0.0	
401	0.0	34.0	1.0	2.0	Chowchilla	CA	0.0	0.0	2.0	0.0	
402	0.0	28.0	1.0	1.0	Oshkosh	WI	0.0	0.0	0.0	1.0	

403 rows × 18 columns

In [ ]:

```python
# median imputation for missing City Data
test_merge = test_merge.fillna(test_merge.median(numeric_only=True))
test_merge
```

Out[ ]:

	manner_of_death	age	gender	race	city	state	signs_of_mental_illness	threat_level	flee	body_camera	p
0	0.0	54.0	1.0	1.0	Southaven	MS	0.0	0.0	2.0	0.0	
1	0.0	41.0	1.0	2.0	Southaven	MS	0.0	0.0	2.0	0.0	
2	0.0	50.0	1.0	5.0	Millston	WI	1.0	0.0	2.0	1.0	
3	0.0	28.0	1.0	2.0	Charlotte	NC	0.0	1.0	0.0	0.0	
4	0.0	25.0	1.0	5.0	Charlotte	NC	1.0	1.0	2.0	0.0	
...	...	...	...	...	...	...	...	...	...	...	
398	0.0	16.0	1.0	1.0	Marion	AR	0.0	2.0	2.0	0.0	
399	0.0	25.0	1.0	1.0	Dayton	OH	0.0	0.0	0.0	0.0	
400	0.0	39.0	1.0	1.0	Homer	LA	0.0	0.0	0.0	0.0	
401	0.0	34.0	1.0	2.0	Chowchilla	CA	0.0	0.0	2.0	0.0	
402	0.0	28.0	1.0	1.0	Oshkosh	WI	0.0	0.0	0.0	1.0	

403 rows × 18 columns

In [ ]:

```
test_merge.isnull().sum()
```

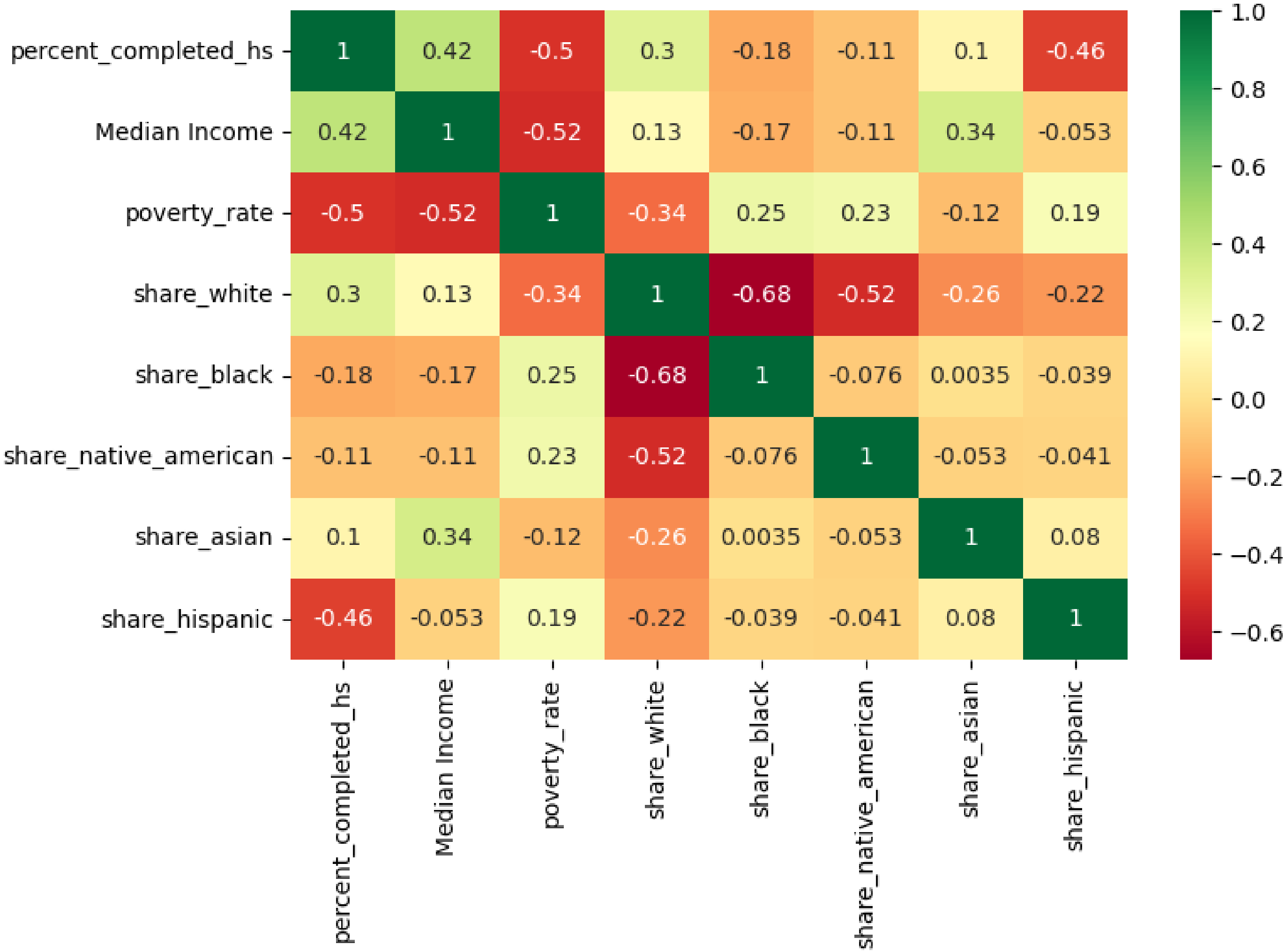
Out[ ]:

```
manner_of_death            0
age                        0
gender                     0
race                       0
city                       0
state                      0
signs_of_mental_illness    0
threat_level               0
flee                       0
body_camera                0
percent_completed_hs       0
Median Income              0
poverty_rate               0
share_white                0
share_black                0
share_native_american      0
share_asian                0
share_hispanic             0
dtype: int64
```

Correlation Heat Map

In [ ]:

```
plt.subplots(figsize=(8, 5))
sns.heatmap(merged.drop(['state', 'city'],axis=1).corr(), annot=True, cmap="RdYlGn")
plt.show()
```



From the heat map above, we can see that

- **percent_completed_hs** has
  - **moderate positive correlation** (0.42) with **Median Income**
  - **moderate negative correlation** (-0.5) with **poverty_rate**
  - **moderate negative correlation** (-0.46) with **share_hispanic**
- **Median Income** has
  - **moderate negative correlation** (-0.52) with **poverty_rate**
- **share_white**
  - **strong negative correlation** (-0.68) with **share_black**
  - **moderate negative correlation** (-0.52) with **share_native_american**

Possible explanations:

- percent_completed_hs:
  - community with higher educated rate may have a higher median income
  - community with higher educated rate may have a lower poverty rate
  - community with higher educated rate may have a lower percentage of hispanic members
- Median Income:
  - community with higher median income may have a much lower poverty rate
- share_white:
  - community with higher percentage of white members may imply a much lower percentage of black members
  - community with higher percentage of white members may have a lower percentage of hispanic members

> Based on the correlation heat map, we can select some features from **City Data** with low correlations. The following subsets of features are tested.

In [ ]:
```
# 1. Max accu = 0.55, Max f1 = 0.56 in RForst
#    NBayes:    accu = 0.48, f1 = 0.50
#    KNN:       accu = 0.42, f1 = 0.45
#    RForest:   accu = 0.55, f1 = 0.56
#    GradientB: accu = 0.41, f1 = 0.48
# features = ['percent_completed_hs','share_white', 'share_asian']

# 2. Max accu = 0.56, Max f1 = 0.60 in NBayes
#    NBayes:    accu = 0.56, f1 = 0.60
#    KNN:       accu = 0.53, f1 = 0.54
#    RForest:   accu = 0.54, f1 = 0.55
#    GradientB: accu = 0.53, f1 = 0.56
# features = ['percent_completed_hs','share_black', 'share_native_american','share_asian','share_hispanic']

# 3. Max accu = 0.52, Max f1 = 0.53 in RForst
#    NBayes:    accu = 0.39, f1 = 0.40
#    KNN:       accu = 0.37, f1 = 0.39
#    RForest:   accu = 0.52, f1 = 0.53
#    GradientB: accu = 0.39, f1 = 0.46
# features = ['Median Income','share_white', 'share_asian']

# 4. Max accu = 0.57 in RForest, Max f1 = 0.59 in NBayes
#    NBayes:    accu = 0.56, f1 = 0.59
#    KNN:       accu = 0.39, f1 = 0.42
#    RForest:   accu = 0.57, f1 = 0.57
#    GradientB: accu = 0.51, f1 = 0.55
# features = ['Median Income','share_black', 'share_native_american','share_asian','share_hispanic']

# 5. Max accu = 0.45 in RForest, Max f1 = 0.48 in NBayes
#    NBayes:    accu = 0.44, f1 = 0.48
#    KNN:       accu = 0.41, f1 = 0.44
#    RForest:   accu = 0.45, f1 = 0.47
#    GradientB: accu = 0.36, f1 = 0.44
# features = ['poverty_rate', 'share_white', 'share_asian']

# 6. Max accu = 0.53 in RForest, Max f1 = 0.56 in GradientB
#    NBayes:    accu = 0.49, f1 = 0.53
#    KNN:       accu = 0.53, f1 = 0.54
#    RForest:   accu = 0.53, f1 = 0.54
#    GradientB: accu = 0.52, f1 = 0.56
# features = ['poverty_rate', 'share_black', 'share_native_american','share_asian','share_hispanic']

# 7. Max accu = 0.43 in NBayes, Max f1 = 0.44 in KNN
#    NBayes:    accu = 0.43, f1 = 0.43
#    KNN:       accu = 0.40, f1 = 0.44
#    RForest:   accu = 0.42, f1 = 0.44
#    GradientB: accu = 0.34, f1 = 0.41
# features = ['share_white','share_asian']

# 8. Max accu = 0.50, Max f1 =0.54 in GradientB
#    NBayes:    accu = 0.41, f1 = 0.44
#    KNN:       accu = 0.42, f1 = 0.44
#    RForest:   accu = 0.48, f1 = 0.49
#    GradientB: accu = 0.50, f1 = 0.54
# features = ['share_black', 'share_native_american','share_asian','share_hispanic']

# 9. Max accu = 0.57, Max f1 = 0.59 in NBayes
#    NBayes:    accu = 0.57, f1 = 0.59
#    KNN:       accu = 0.52, f1 = 0.54
#    RForest:   accu = 0.55, f1 = 0.55
#    GradientB: accu = 0.52, f1 = 0.54
features = ['percent_completed_hs','share_black', 'share_native_american', 'share_hispanic']

features
```

Out[ ]:
```
['percent_completed_hs',
 'share_black',
 'share_native_american',
 'share_hispanic']
```

> We can also add some other features from **Victim Data**, the following subsets of features are tested:

In [ ]:
```python
added = []
# a. no improvement in 2+a
# added = ['manner_of_death']

# b. small improvement in 2+b
#    Max accu = 0.58, Max f1 =0.61 in NBayes
#    NBayes:     accu = 0.58, f1 = 0.61
#    KNN:        accu = 0.53, f1 = 0.55
#    RForest:    accu = 0.56, f1 = 0.55
#    GradientB: accu = 0.54, f1 = 0.59
# added = ['age']

# c. no improvement in 2+c
# added = ['gender']

# d. no improvement in 2+d
# added = ['threat_level']

# e. no improvement in 2+e
# added = ['flee']

# f. no improvements in 2+f
# added = ['body_camera']

# add to the features
features = features + added
features
```

Out[ ]:
```
['percent_completed_hs',
 'share_black',
 'share_native_american',
 'share_hispanic']
```

> According to the accuracy and weighted average f1 score in the cell above, features with `[` 'percent_completed_hs','share_black', 'share_native_american', 'share_hispanic' `]` produce the greatest accuracy and f1 scores with relatively small amount of features. Although features number 2, which contains one more feature 'share_asian' than features number 9, the accuracy and f1 scores do not improve a lot. With added features (a to f), we did not see any huge improvement.Therefore, based on Occam's Razor, we prefer the simpler one.

Data Spliting

In [ ]:
```python
X_train = train_merge[features]
X_train
```

Out[ ]:

	percent_completed_hs	share_black	share_native_american	share_hispanic
0	57.8	0.8	1.0	69.0
1	57.8	0.8	1.0	69.0
2	57.8	0.8	1.0	69.0
3	57.8	0.8	1.0	69.0
4	57.8	0.8	1.0	69.0
...	...	...	...	...
5971	98.4	0.1	0.4	1.9
5972	93.2	11.5	0.4	1.6
5973	90.8	18.5	0.2	2.0
5974	85.1	6.7	0.7	18.4
5975	83.5	12.6	0.4	6.6

5976 rows × 4 columns

In [ ]:

```
Y_train = train_merge['race']
Y_train
```

Out[ ]:

```
0       0.0
1       0.0
2       0.0
3       0.0
4       0.0
       ...
5971    5.0
5972    5.0
5973    5.0
5974    5.0
5975    5.0
Name: race, Length: 5976, dtype: float64
```

In [ ]:

```
X_test = test_merge[features]
X_test
```

Out[ ]:

	percent_completed_hs	share_black	share_native_american	share_hispanic
0	88.4	22.2	0.3	5.0
1	88.4	22.2	0.3	5.0
2	82.0	0.0	3.2	2.4
3	88.4	35.0	0.5	13.1
4	88.4	35.0	0.5	13.1
...	...	...	...	...
398	89.3	28.0	0.4	2.0
399	82.1	42.9	0.3	3.0
400	79.0	64.3	0.1	1.4
401	68.3	12.6	2.0	37.8
402	89.3	3.1	0.8	2.7

403 rows × 4 columns

In [ ]:
```
Y_test = test_merge["race"]
Y_test
```

Out[ ]:
```
0      1.0
1      2.0
2      5.0
3      2.0
4      5.0
      ...
398    1.0
399    1.0
400    1.0
401    2.0
402    1.0
Name: race, Length: 403, dtype: float64
```

In [ ]:
```
X_train.shape, Y_train.shape
```

Out[ ]:
```
((5976, 4), (5976,))
```

In [ ]:
```
X_test.shape, Y_test.shape
```

Out[ ]:
```
((403, 4), (403,))
```

Model Predictions and Evaluations

In [ ]:
```
# imports evaluation functions
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score
# from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score
```

Naive Bayes

In [ ]:
```
# Imports
from sklearn.naive_bayes import MultinomialNB
```

In [ ]:
```
# Fit the Naive Bayes classifier
nb_clf = MultinomialNB().fit(X_train, Y_train)
# Predict the race values for the test set
Y_test_predicted = nb_clf.predict(X_test)
# Compare the predictions to the labels for test set
print('Accuracy: ', accuracy_score(Y_test, Y_test_predicted))
print('Classification report: ')
print(classification_report(Y_test, Y_test_predicted,target_names=race_map.classes_.tolist(),zero_division=1))
```

```
Accuracy:  0.565756823821340
Classification report: 
              precision    recall  f1-score   support

           A       0.00      0.00      0.00         8
           B       0.57      0.48      0.52       111
           H       0.57      0.53      0.55        75
           N       0.19      0.75      0.30         4
           O       0.00      1.00      0.00         0
           W       0.71      0.64      0.67       205

    accuracy                           0.57       403
   macro avg       0.34      0.57      0.34       403
weighted avg       0.62      0.57      0.59       403
```

K-Nearest Neighbors

```
In [ ]: # Imports
        from sklearn.neighbors import KNeighborsClassifier
```

```
In [ ]: # Fit the K-Nearest Neighbors classifier
        knn_clf = KNeighborsClassifier(n_neighbors=7, weights="distance").fit(X_train, Y_train)
        # Predict the race values for the test set
        Y_test_predicted = knn_clf.predict(X_test)
        # Compare the predictions to the labels for test set
        print('Accuracy: ', accuracy_score(Y_test, Y_test_predicted))
        print('Classification report: ')
        print(classification_report(Y_test, Y_test_predicted, target_names=race_map.classes_.tolist(),zero_division=1
```

```
Accuracy:  0.5235732009925558
Classification report:
              precision    recall  f1-score   support

           A       0.00      0.00      0.00         8
           B       0.48      0.42      0.45       111
           H       0.48      0.52      0.50        75
           N       0.18      0.50      0.27         4
           O       0.00      1.00      0.00         0
           W       0.66      0.60      0.63       205

    accuracy                           0.52       403
   macro avg       0.30      0.51      0.31       403
weighted avg       0.56      0.52      0.54       403
```

Random Forest

```
In [ ]: # Imports
        from sklearn.ensemble import RandomForestClassifier
```

```
In [ ]: # Fit the K-Nearest Neighbors classifier
        rf_clf = RandomForestClassifier(n_estimators=15, bootstrap=True).fit(X_train, Y_train)
        # Predict the race values for the test set
        Y_test_predicted = rf_clf.predict(X_test)
        # Compare the predictions to the labels for test set
        print('Accuracy: ', accuracy_score(Y_test, Y_test_predicted))
        print('Classification report: ')
        print(classification_report(Y_test, Y_test_predicted, target_names=race_map.classes_.tolist(),zero_division=1
```

```
Accuracy:  0.5409429280397022
Classification report:
              precision    recall  f1-score   support

           A       0.00      0.00      0.00         8
           B       0.50      0.35      0.41       111
           H       0.53      0.44      0.48        75
           N       0.20      0.50      0.29         4
           O       0.00      1.00      0.00         0
           W       0.63      0.70      0.67       205

    accuracy                           0.54       403
   macro avg       0.31      0.50      0.31       403
weighted avg       0.56      0.54      0.54       403
```

Gradient Boosting

```
In [ ]: # Imports
        from sklearn.ensemble import GradientBoostingClassifier
```

```
In [ ]: # Fit the Gradient Boosting classifier
        gb_clf = GradientBoostingClassifier(n_estimators=100, learning_rate=0.01, max_depth=3).fit(X_train, Y_train)
```

```python
# Predict the race values for the test set
Y_test_predicted = gb_clf.predict(X_test)
# Compare the predictions to the labels for test set
print('Accuracy: ', accuracy_score(Y_test, Y_test_predicted))
print('Classification report: ')
print(classification_report(Y_test, Y_test_predicted, target_names=race_map.classes_.tolist(),zero_division=1
```

```
Accuracy:  0.5161290322580645
Classification report:
              precision    recall  f1-score   support

           A       0.00      0.00      0.00         8
           B       0.50      0.52      0.51       111
           H       0.55      0.47      0.50        75
           N       0.09      1.00      0.16         4
           O       0.00      1.00      0.00         0
           W       0.69      0.54      0.60       205

    accuracy                           0.52       403
   macro avg       0.30      0.59      0.30       403
weighted avg       0.59      0.52      0.54       403
```

> The results of the trained machine learning classifiers demonstrate that we do have a reasonable ability to predict a victim's race given adequate police data about a victim and corresponding city data. Our machine learning classifiers achieved F1-scores and accuracies of 0.56-0.57 during several of the runs. This is significant because the classifiers are multi-class predictors, where it is predicting a race class from 6 different possible races. The baseline would be "random guessing", which would result in an accuracy of "1 in 6" on average, or 0.1667. The models we have built and trained are clearly significantly better at predicting race than simply random guessing. Also, while the classes are imbalanced prior to our up-sampling of the training data(there are several more white victims than asian victims for example), one may think that a classifier that simply predicts "white" for all victims would have 51% accuracy (as ~51% of the victims were white) which appears similar to the Gradient Boosting model, however this "assign everyone the label 'white'" model is obviously bad and would demonstrate such through an F1-score of 0. Accuracy is not the best metric for understanding the efficacy of a machine learning model, and so we value greatly the F1-score to understand how well the model performs on the minority classes (labels that are infrequent). Thanks to the up-sampling and feature reduction, we were able to train a simpler model on balanced class data, improving the f1-scores and accuracies of our classifiers across the board.