Behind the Bullet: Data Insights into Shootings

The issues:

The Washington Post shared data about police shootings in the United States. This data includes information like when and where the shootings happened, details about the people involved (like their age, gender, and race), whether they had mental health issues, and other important information. The dataset also has information about the police departments involved and whether they had body cameras. This data helps researchers and policymakers understand patterns and trends in police shootings. We come across the following issues.

1. Who gets involved in shootings by age?
2. Why do different racial groups have varying involvement in shootings?
3. Are there patterns in shootings over different years and months?
4. Why are most shootings involving males, and how can this be addressed?
5. How do the levels of threat impact incidents?
6. What do we learn from analyzing how people flee during incidents?
7. Why is the presence of body cameras important, and how should they be used?
8. How can clustering help pinpoint areas for specific interventions? What clustering techniques are used?
9. What can decision trees teach us about predicting behavior during incidents?

Findings:

1. **Age Distribution**: The age distribution of individuals involved in shootings shows a median age of 35, with a wide range from 2 to 92.
2. **Race Disparities**: There are significant disparities in the racial distribution of individuals involved in shootings. Whites (W) have the highest frequency (3300), followed by Blacks (B) (1766) and Hispanics (H) (1166). Other racial groups, including Asians (A), Native Americans (N), and Others (O), have fewer occurrences.
3. **Temporal Patterns**: Shootings exhibit variations over the years and months. The year 2015 had the highest frequency (918), while 2021 had the lowest (350). Monthly distributions also differ, with March having the highest frequency (512).
4. **Gender Disparity**: Most individuals involved in shootings are male (7613), indicating a gender imbalance. Female (F) involvement is relatively low (358), with some cases of unknown gender (Unknown, 31).
5. **Threat Levels**: Shootings are categorized into different threat levels, with "attack" being the most common (5010), followed by "other" (2663), and "undetermined" (329).
6. **Fleeing Behavior**: The analysis of fleeing behavior reveals that "Not fleeing" is the most common response (4430), followed by "Car" (1289), "Foot" (1022), and "Other" (295).
7. **Body Camera Presence**: In a majority of cases, body cameras were not present (6865), while in others, they were used (1137).

8. **Clustering Analysis**: Different clustering techniques, including K-Means, DBSCAN, and K-Medoids, were applied to identify patterns within the data. K-Means grouped incidents into 10 clusters, focusing on locations but not well-suited for odd-shaped areas. DBSCAN found 99 clusters, better for irregular patterns. K-Medoids, also with 10 clusters, balanced detail and reliability, handling outliers better.
9. **Decision Tree Analysis**: A decision tree model was constructed to predict fleeing behavior using factors like signs of mental illness, gender, race, threat level, body camera presence, and armed status. The model achieved an accuracy of 67%, offering insights into the factors influencing an individual's behavior during these incidents.

Confusion Matrix Findings:

- True Positives (TP): The number of cases correctly predicted as "fleeing" is 37 for "Not fleeing," 1 for "Car," and 676 for "Other." This indicates the model's ability to accurately identify instances where individuals were indeed fleeing.
- True Negatives (TN): The model correctly predicted 5010 cases as "Not fleeing," indicating its effectiveness in identifying situations where individuals were not fleeing.
- False Positives (FP): There were 3 cases where the model incorrectly predicted "fleeing" when the actual behavior was "Not fleeing." Additionally, there were 136 cases incorrectly predicted as "fleeing" when the actual behavior was "Car," and 33 cases incorrectly predicted as "fleeing" when the actual behavior was "Other."

- <u>False Negatives (FN):</u> There were 7 cases where the model incorrectly predicted "Not fleeing" when the actual behavior was "fleeing." Similarly, there were 14 cases incorrectly predicted as "Not fleeing" when the actual behavior was "Car."

These findings provide valuable information for understanding the demographics, temporal trends, and factors associated with shootings, which can inform policy decisions and law enforcement strategies to address potential disparities and improve incident outcomes.

Discussions:

Age Distribution:

Shootings happen to people of all ages, from very young (2 years old) to elderly (92 years old), with most of them being around 35 years old on average. This shows that shootings don't discriminate by age, and we should have policies and services that can help people of all ages affected by these incidents.

Race Disparities:

There are big differences in the number of shootings among different racial groups. White people have the most shootings, followed by Black and Hispanic people. This shows that there's a problem with racial inequality, and we need fair policies to reduce these differences and make things more equal for everyone.

Temporal Patterns:

Looking at how shootings happen over the years and months, we don't see a clear pattern of shootings always going up or down. Instead, it goes up and down at different times. This means that police should be ready to act in specific areas where shootings might happen more often, and they should try to prevent them.

Gender Disparity:

Most of the people involved in shootings are men, and this shows there's a big difference between men and women in these incidents. We need to look more into why this is happening and think about how we can make things fairer between men and women in these situations. Policymakers should make sure their plans take into account these gender differences and work towards making things more equal for everyone.

Threat Levels:

Shootings are divided into different levels of danger, and "attack" is the most common one. Knowing these threat levels can help the police get ready for different kinds of situations and know how to respond when things get tough. It's important that the rules and training they have match up with these threat levels so they can handle each situation the right way.

Fleeing Behavior:

Looking at how people act when a shooting happens tells us important things. Most people don't try to run away, but some do, either by using a car, running on foot, or other ways. This helps the police know how to train and make plans for dealing with people who try to run away during these incidents.

Body Camera Presence:

Whether or not police officers have body cameras when incidents occur is important for being clear and accountable. Most of the time, they don't have these cameras. This suggests that there should be clear rules about when and how to use them, so we can be sure about what happens during police encounters.

Cluster Analysis:

The application of advanced techniques like clustering helps uncover hidden patterns within the data. These patterns can inform more targeted approaches to addressing different types of incidents, contributing to more effective interventions.

K-Means Clustering: K-Means sorted shootings into 10 groups based on where they happened. However, it assumes that these groups are all round and have about the same number of shootings. In real life, shootings might cluster in irregular shapes or be more concentrated in some areas. K-Means is still useful because it gives a general idea of where shootings occur more frequently, helping law enforcement decide where to allocate resources.

DBSCAN Clustering: DBSCAN is like a detective. It found 99 different patterns in the data. It doesn't assume all shootings are the same; it looks for clusters of different shapes and sizes. These clusters could represent specific neighborhoods or places where shootings are more common. DBSCAN is like finding hidden hotspots or areas where extra attention is needed to reduce shootings.

K**-Medoids Clustering:** K-Medoids is similar to K-Means, but it's better at handling unusual situations. It grouped shootings into 10 clusters, but it's less sensitive to weird data points. This helps in cases where there might be unusual patterns in the data. K-Medoids helps law enforcement identify areas with consistent shooting patterns and make smarter decisions about where to focus their efforts.

Decision Tree Analysis:

The decision tree analysis helps us understand the complex relationships between factors like mental illness, gender, race, threat level, body camera presence, and armed status in predicting fleeing behavior. This knowledge can lead to better training and response strategies for law enforcement.

- Accuracy is a metric used to measure the overall performance of a classification model. In our case, the accuracy of the decision tree model was 0.67, which means that the model correctly predicted whether an individual would flee or not in 67% of cases.
- The confusion matrix provides a more detailed breakdown of the model's predictions. It shows the number of true positive (correctly predicted fleeing), true negative (correctly predicted not fleeing), false positive (predicted fleeing but not fleeing), and false negative (predicted not fleeing but fleeing) cases.

In simple terms, these findings help law enforcement and policymakers understand who's affected, where incidents happen, and why. It also helps them create fair rules, plan better, and improve training for law enforcement officers.

Appendix A -Methodology:

Data Collection:

The data used in this analysis was collected from **Washington Post data repository on fatal police shootings in the United States** from 2015-2022. The dataset contains information related to shootings, including various attributes such as ID, name, date, manner of death, armed status, age, gender, race, city, state, signs of mental illness, threat level, fleeing status, body camera presence, longitude, latitude, and is_geocoding_exact.

Data Description:

The dataset comprises 8002 entries. While most entries provide information on the date, manner of death, armed status, city, state, signs of mental illness, threat level, fleeing status, body camera presence, and geolocation accuracy, some data fields exhibit missing values. Specifically, names are available for 7548 individuals involved in the incidents, and age information is provided for 7499 of them. Gender is known for 7971 individuals, and race is specified for 6485 individuals. Geospatial information in the form of longitude and latitude coordinates is available for 7162 entries.

Data Preparation:

As there are missing values present in the datasheet, we removed the missing values using the dropna function in Python. It removed the rows which are having empty cells.

Variable Creation:

1. ID: This is a unique identifier for each incident in the dataset.
2. Name: The name of the individual involved in the incident.
3. Date: The date on which the incident occurred.
4. Manner of Death: Describes the manner in which the individual died (e.g., homicide, suicide).
5. Armed: Indicates whether the individual was armed during the incident.
6. Age: The age of the individual at the time of the incident.
7. Gender: The gender of the individual.
8. Race: The racial background of the individual.
9. City: The city where the incident took place.
10. State: The state where the incident occurred.
11. Signs of Mental Illness: Indicates whether there were signs of mental illness in the individual.
12. Threat Level: Describes the perceived threat level of the individual during the incident.
13. Flee: Indicates whether the individual was fleeing at the time of the incident.
14. Body Camera: Indicates whether a body camera was present during the incident.
15. Longitude: The longitude coordinates of the incident location.

16. Latitude: The latitude coordinates of the incident location.
17. Is Geocoding Exact: Indicates the accuracy of geocoding for the incident location.

Analytic Methods:

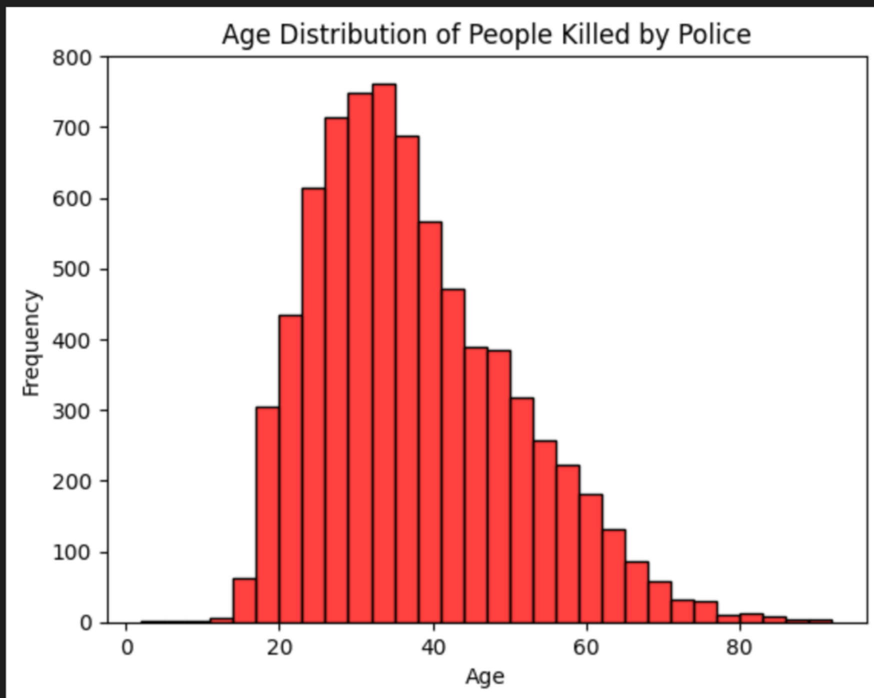
1. **<u>Age Distribution:</u>**
   - To analyze the age distribution of individuals involved in shootings, we used descriptive statistics such as mean, median, and standard deviation. We also created visualizations, including histograms and kernel density plots, to visualize the distribution and assess if it follows a normal distribution.
2. **<u>Race-Based Age Analysis:</u>**
   - To understand how ages vary among different racial groups, we created smoothed histograms for each race and performed statistical tests to identify significant differences in age distributions among races.
3. **<u>Yearly and Monthly Statistics:</u>**
   - To examine trends over time, we computed yearly and monthly statistics of shootings, including counts and trends. We utilized bar charts to visualize these trends.
4. **<u>Gender Distribution:</u>**
   - We analyzed the gender distribution of individuals involved in shootings, calculating percentages and creating bar graphs to illustrate the gender distribution.

5. **State-wise and City-wise Distribution:**
    - For geographical analysis, we presented state-wise and city-wise distribution of shootings. We used bar charts to visualize these distributions.

6. **Clustering Analysis:**
    - We applied clustering techniques, including DBSCAN, K-Means, and K-Medoids, to identify potential patterns or clusters in the data based on selected features.
    - DBSCAN is a clustering algorithm that groups data points based on their density. It identifies clusters as areas with a high density of data points separated by areas with lower densities.
    - K-Means is a popular clustering algorithm that partitions data points into a pre-defined number of clusters (K) based on their similarity.
    - K-Medoids is similar to K-Means but uses medoids (the most central data point in a cluster) instead of centroids to define clusters. This makes K-Medoids more robust to outliers.
7. **Decision Tree Analysis:**
    - We constructed a decision tree model using features such as signs_of_mental_illness, gender, race, threat_level, body_camera, and armed to predict the target variable 'flee'. Described how useful the Decision tree is for understanding how different factors relate to whether someone tries to run away during an incident.

Appendix B - Results:

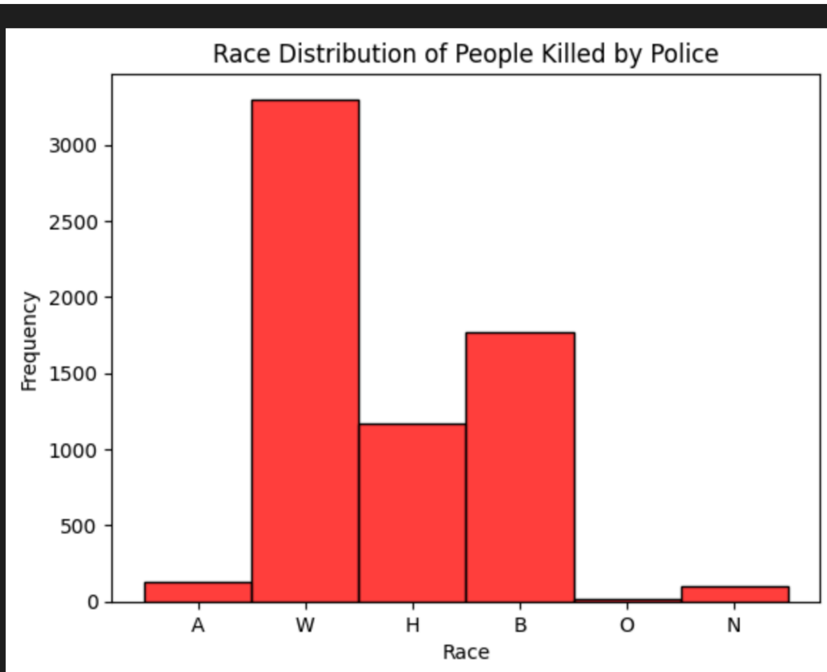
Age Distribution:




```
Minimum Age (min_age): 2.0
Maximum Age (max_age): 92.0
Mean Age (mean_age): 37.20922789705294
Median Age (median_age): 35.0
Standard Deviation of Age (std_dev_age): 12.97948974722669
Skewness of Age (skewness_age): 0.7286010730037696
Kurtosis of Age (kurtosis_age): 0.2327849850362873
```

The analysis of age-related statistics among individuals involved in shootings reveals a diverse age range, spanning from as young as 2 years old to as old as 92 years. The average age of approximately 37.21 years indicates a broad distribution. While the median age of 35 years suggests a central tendency, the moderate right skew (skewness of approximately 0.73) hints at a slightly higher frequency of younger individuals affected by these incidents. The relatively flat kurtosis (approximately 0.23) implies that the age distribution has lighter tails compared to a normal distribution.

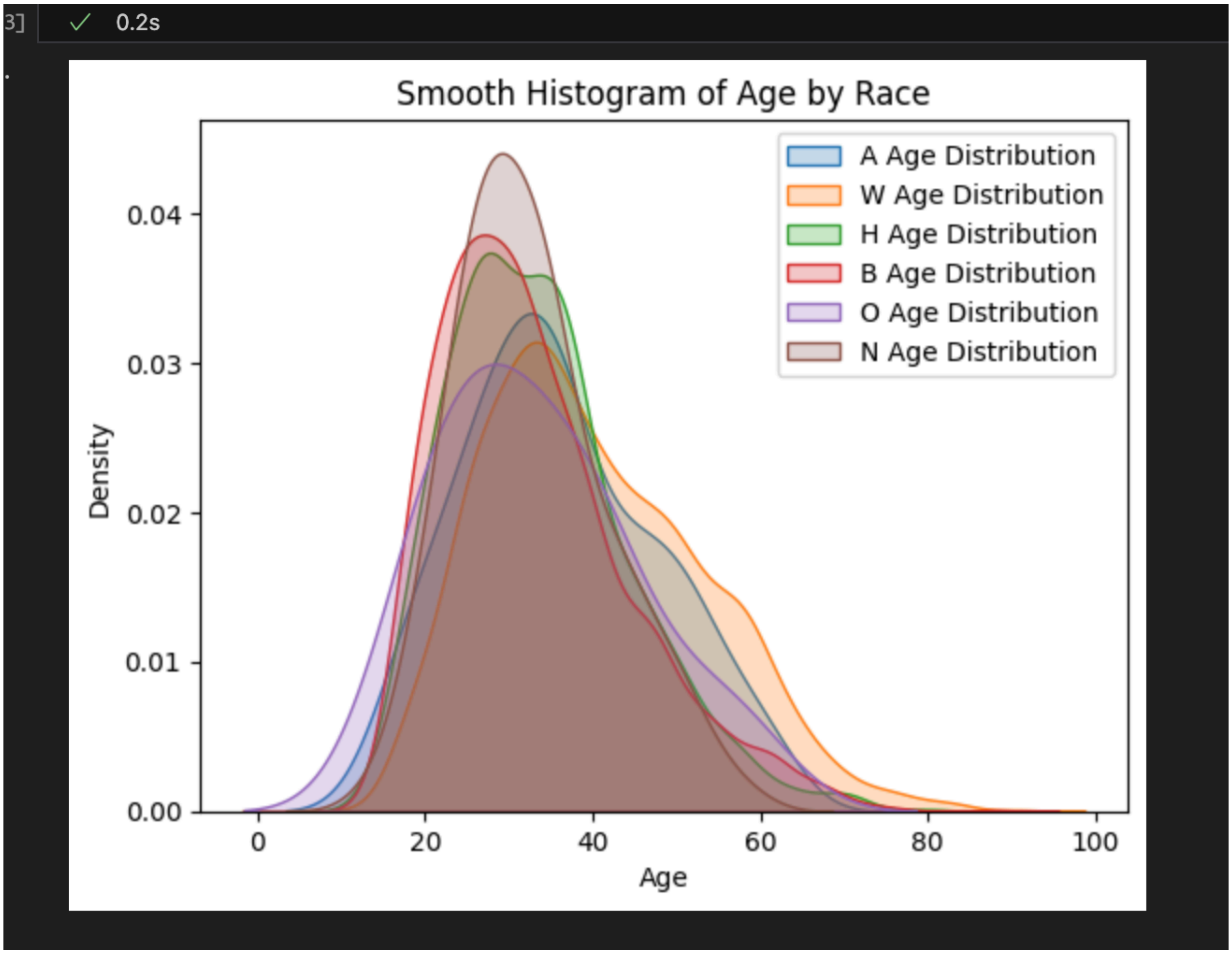
Race Distribution:




```
Race: W, Frequency: 3300
Race: B, Frequency: 1766
Race: H, Frequency: 1166
Race: A, Frequency: 129
Race: N, Frequency: 105
Race: O, Frequency: 19
```

The analysis of racial demographics among individuals involved in these incidents reveals a distribution where the majority of cases are of White (W) individuals, accounting for 3,300 incidents. Black (B) individuals follow with 1,766 incidents, while Hispanic (H) individuals are the next largest group with 1,166 incidents. Asian (A) individuals were involved in 129 incidents, Native American (N) individuals in 105 incidents, and Other (O) races in 19 incidents.

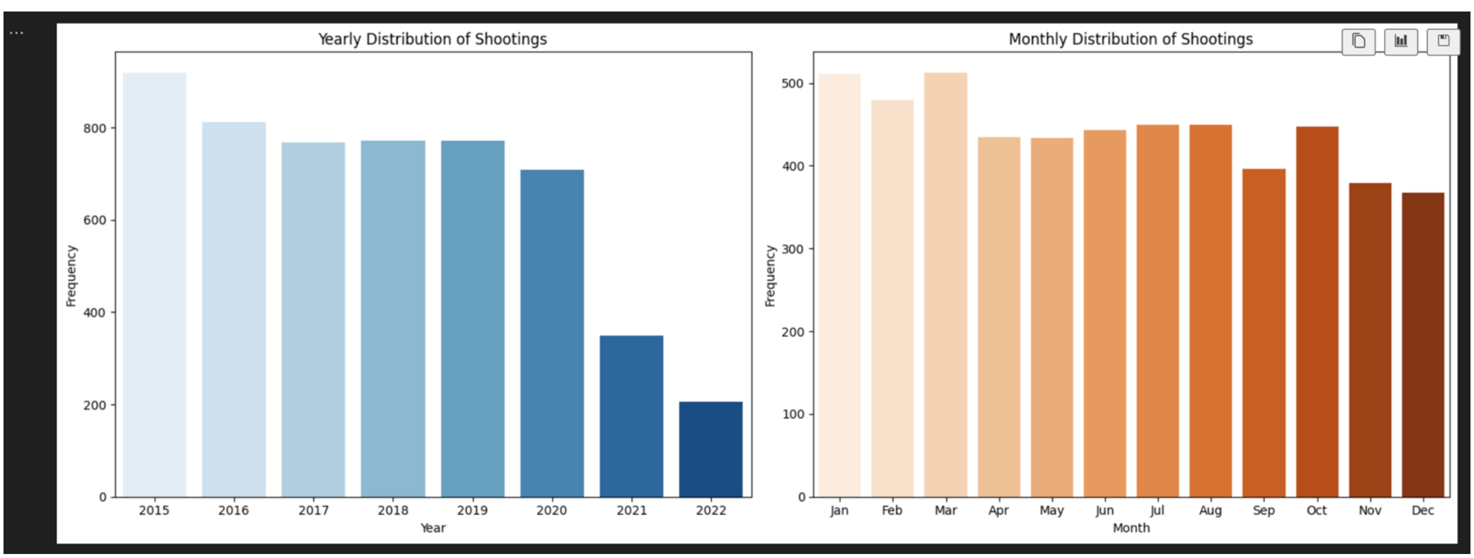
Age by Race distribution:



The analysis of age statistics among different racial groups provides valuable insights into the demographics of individuals involved in these incidents. Among the racial groups, Asians (A) have a median age of 35.0 years and an average age of 35.96 years, with a standard deviation of 11.59. Whites (W) exhibit a median age of 38.0 years and an average age of 40.13 years, with a standard deviation of 13.16. Hispanics (H) have a median age of 32.0 years and an average age of 33.59 years, with a standard deviation of 10.74. Blacks (B) show a median age of 31.0 years and an average age of 32.93 years, with a standard deviation of 11.39. Other races (O) have a median age of 31.0 years and an average age of 33.47 years, with a standard deviation of 11.80. Native Americans (N) exhibit a median age of 32.0 years and an average age of 32.65 years, with a standard deviation of 8.99.

```
...  {'A': {'Median': 35.0,
       'Mean': 35.96,
       'Standard Deviation': 11.592127473196571},
      'W': {'Median': 38.0,
       'Mean': 40.12546239210851,
       'Standard Deviation': 13.162144214944693},
      'H': {'Median': 32.0,
       'Mean': 33.59082892416226,
       'Standard Deviation': 10.743504970329493},
      'B': {'Median': 31.0,
       'Mean': 32.92811594202899,
       'Standard Deviation': 11.38864900700022},
      'O': {'Median': 31.0,
       'Mean': 33.473684210526315,
       'Standard Deviation': 11.796272580083325},
      'N': {'Median': 32.0,
       'Mean': 32.650485436893206,
       'Standard Deviation': 8.994234251009962}}
```

Yearly-Monthly Statistics:

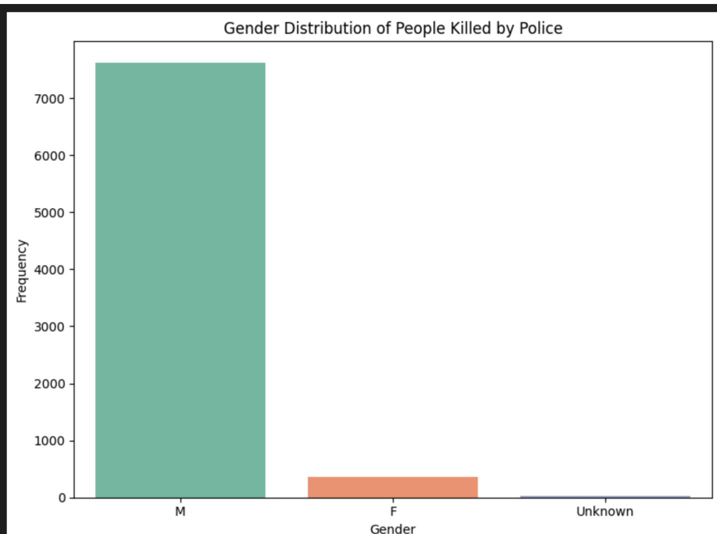


```
Yearly Distribution:
Year: 2015, Frequency: 918
Year: 2016, Frequency: 811
Year: 2017, Frequency: 767
Year: 2018, Frequency: 771
Year: 2019, Frequency: 771
Year: 2020, Frequency: 709
Year: 2021, Frequency: 350
Year: 2022, Frequency: 206

Monthly Distribution:
Month: Jan, Frequency: 511
Month: Feb, Frequency: 479
Month: Mar, Frequency: 512
Month: Apr, Frequency: 435
Month: May, Frequency: 434
Month: Jun, Frequency: 443
Month: Jul, Frequency: 450
Month: Aug, Frequency: 450
Month: Sep, Frequency: 396
Month: Oct, Frequency: 447
Month: Nov, Frequency: 379
Month: Dec, Frequency: 367
```

Looking at the yearly data, we can see that the number of incidents has changed over time. In 2015, there were 918 incidents, and it gradually decreased over the years. In 2022, there were 206 incidents.

When we look at the data by month, we notice that some months have more incidents than others. March had the most incidents with 512, followed by January and February. On the other hand, November and December had fewer incidents.

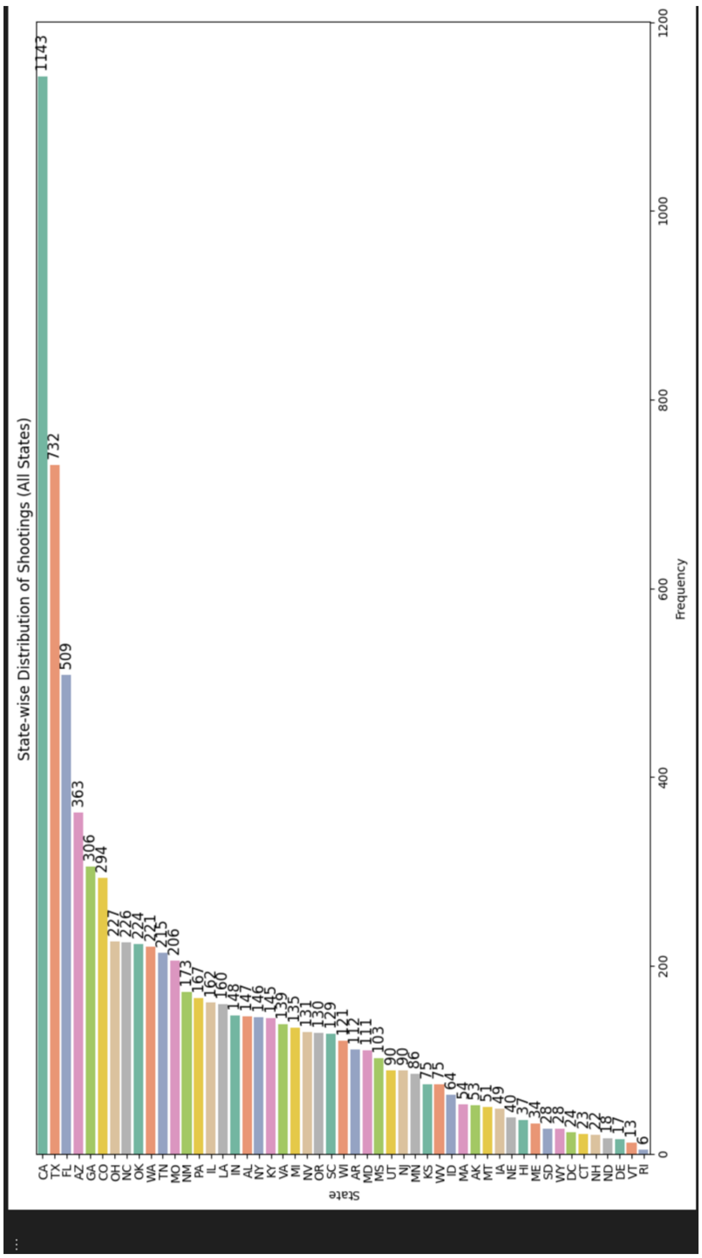
Gender Distribution:

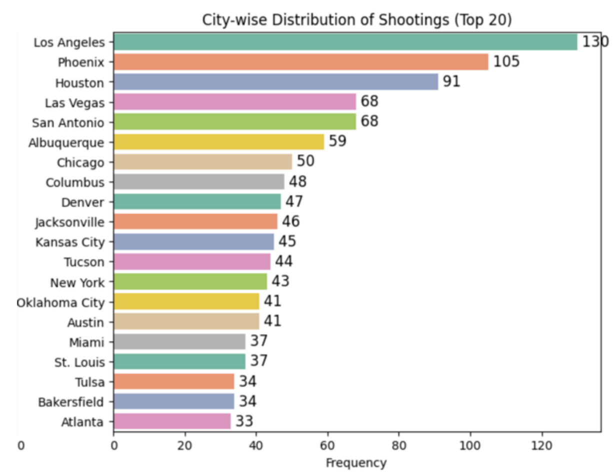



```
Gender Distribution:
Gender: M, Frequency: 7613
Gender: F, Frequency: 358
Gender: Unknown, Frequency: 31
```

The gender distribution of individuals involved in these incidents shows that the majority are males (about 7613 cases), while females are less frequently involved (around 358 cases). There are also a few cases where the gender information is unknown (31 cases)

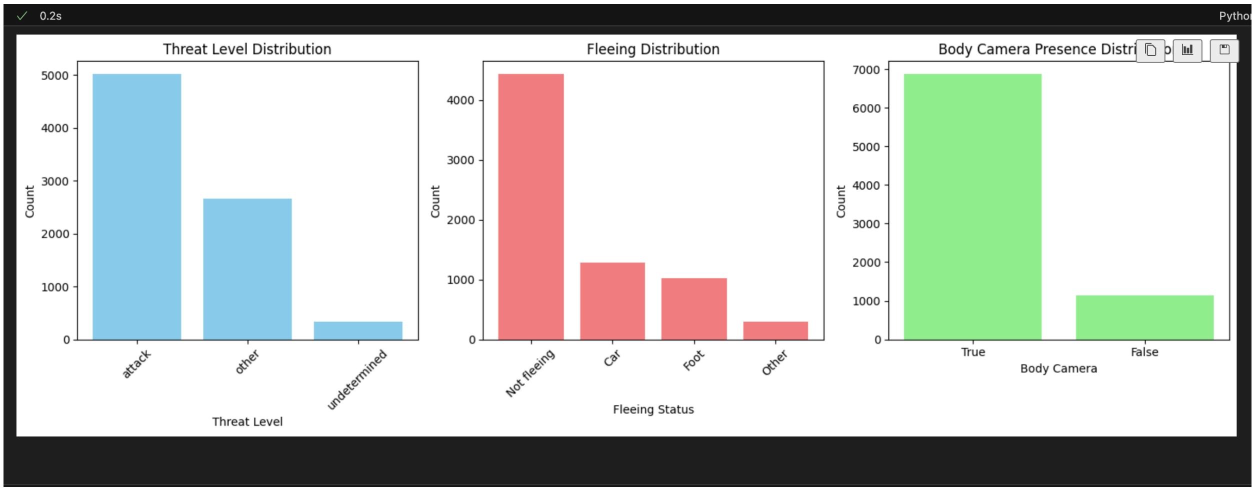
State-wise and City-wise Distribution:





The highest number of deaths are in Los Angeles and the least number of deaths are in Atlanta when we consider city-wise distribution. When we look into state-wise distributions, the highest number of deaths is in California leading more with 1143 and the least number of deaths is in Rhode Island.

Threat level, Fleeing and Body Camera Presence:



In the analysis of threat levels, we found that the most common threat level associated with these incidents is "attack," which occurred in approximately 5010 cases. "Other" threat levels were reported in 2663 cases, while the threat level was "undetermined" in 329 cases.

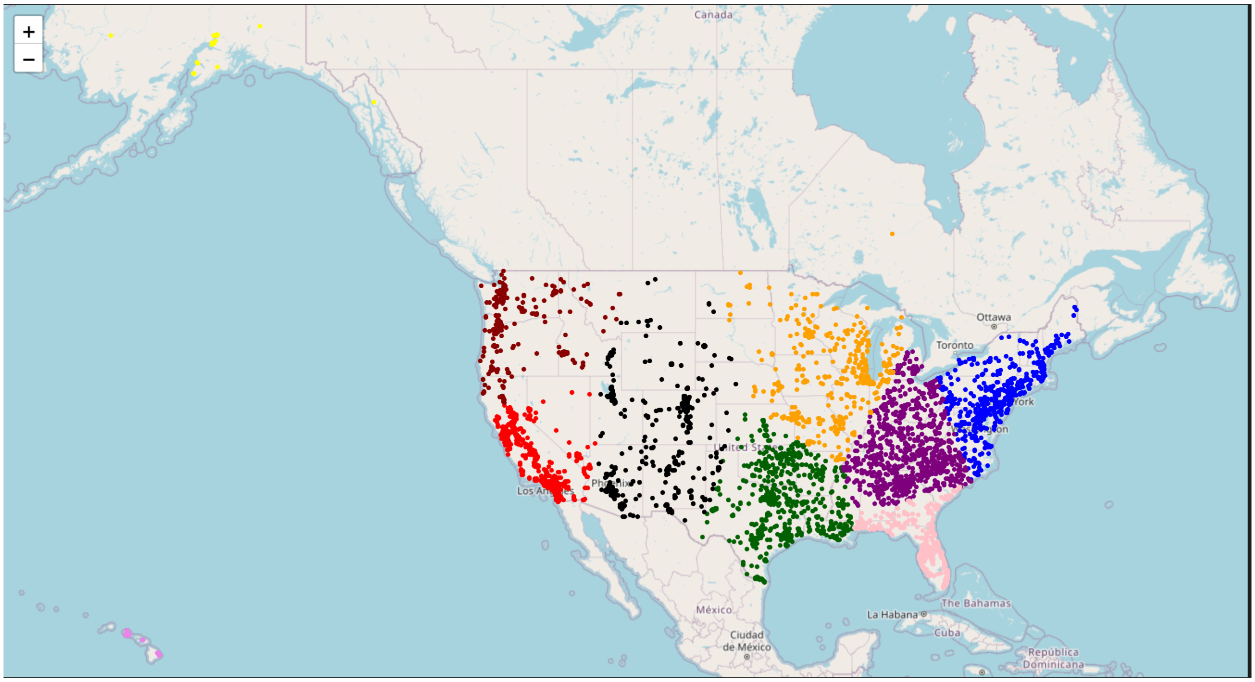
```
Threat Level Distribution:
threat_level
attack          5010
other           2663
undetermined     329
Name: count, dtype: int64

Fleeing Distribution:
flee
Not fleeing    4430
Car            1289
Foot           1022
Other           295
Name: count, dtype: int64

Body Camera Presence Distribution:
body_camera
False    6865
True     1137
Name: count, dtype: int64
```

When examining fleeing behavior, we observed that a majority of individuals involved in these incidents were "Not fleeing" (about 4430 cases). Some individuals were fleeing in a "Car" (1289 cases), while others were on "Foot" (1022 cases), and there were a few cases where the fleeing method was categorized as "Other" (295 cases).

Regarding body camera presence, the analysis revealed that in most cases, there was no body camera present (6865 cases). However, body cameras were present in a significant number of incidents as well (1137 cases).

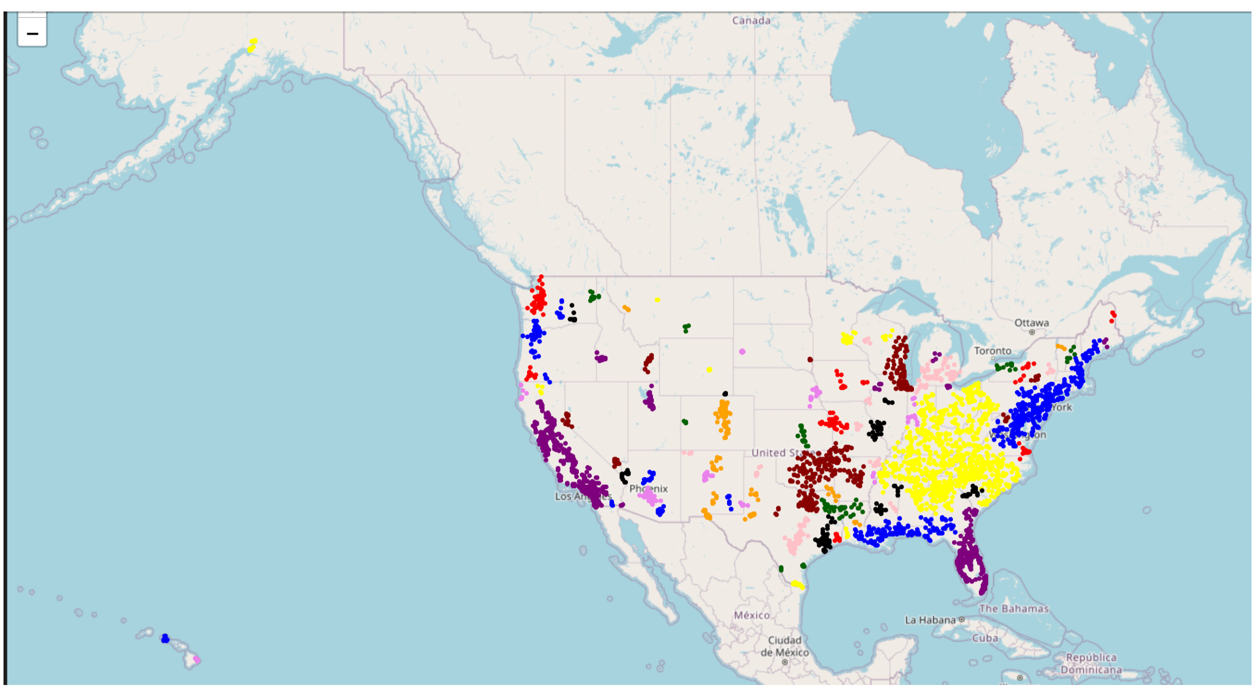
Clustering Analysis:

KMeans Clustering:



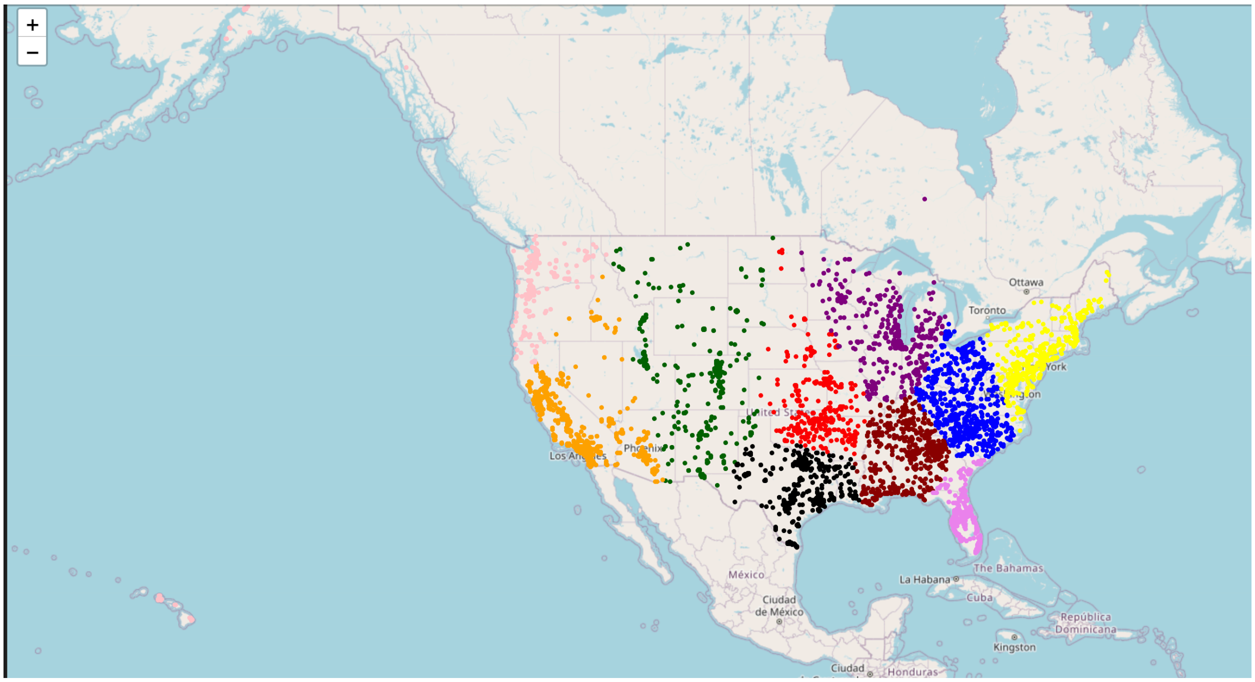

```
...   Number of clusters in  K-Means Clustering: 10
```

DBSCAN Clustering:



```
···   Number of clusters in DBSCAN Clustering: 99
```

K-Medoids Clustering:




```
···   Number of clusters K-Medoids: 10
```

In our clustering analysis, we used three different methods to group similar incidents based on their geographical coordinates. The K-Means clustering method identified 10 clusters, which means it divided the incidents into 10 distinct groups based on their locations. Similarly, the K-Medoids method also resulted in 10 clusters. However, the DBSCAN clustering method produced a higher number of clusters, specifically 99. This indicates that DBSCAN identified more fine-grained groupings of incidents, possibly capturing more localized patterns.

Decision Tree Analysis:

```
...    Accuracy: 0.67
       Confusion Matrix:
       [[ 37   3 125   3]
        [  7   1 136   0]
        [ 21  14 676   0]
        [  3   2  33   0]]
```

In our decision tree analysis, we aimed to predict whether individuals would flee during various incident scenarios, including cases where they did not flee, fled in a car, fled on foot, or in other situations. Our model achieved an accuracy of approximately 67%, indicating its ability to make correct predictions in most cases. However, when examining the confusion matrix, we found that there were some misclassifications. For instance, we correctly predicted 37 incidents where individuals did not flee and 676 incidents where they fled. However, there were cases of misclassification, such as 125 instances where individuals were predicted to flee when they did not, 136 instances involving car-related fleeing, and 33 instances involving fleeing on foot, where our model made incorrect predictions.

Appendix C- Coding:

```
import numpy as np
import pandas as pd
from sklearn.cluster import DBSCAN
import matplotlib.pyplot as plt
import seaborn as sns
from mpl_toolkits.axes_grid1 import make_axes_locatable
from sklearn.cluster import KMeans
import folium
import warnings
import calendar
import matplotlib.pyplot as plt
warnings.filterwarnings("ignore", category=FutureWarning)
```

```python
dataset = pd.read_excel("/Users/tysonmukesh/Desktop/MTH-522/Project-2/Shootings.xls")
from scipy.stats import norm, skew, kurtosis

# Extracting age data and removing missing values
age_data = dataset['age'].dropna()
race_data = dataset['race'].dropna()

# Basic Descriptive Statistics
min_age = age_data.min()
max_age = age_data.max()
mean_age = age_data.mean()
median_age = age_data.median()
std_dev_age = age_data.std()
skewness_age = skew(age_data)
kurtosis_age = kurtosis(age_data)

# Creating the histogram for the age distribution

sns.histplot(age_data, kde=False, color='red', bins=30)
plt.title('Age Distribution of People Killed by Police')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()

print(f"Minimum Age (min_age): {min_age}")
print(f"Maximum Age (max_age): {max_age}")
print(f"Mean Age (mean_age): {mean_age}")
print(f"Median Age (median_age): {median_age}")
print(f"Standard Deviation of Age (std_dev_age): {std_dev_age}")
print(f"Skewness of Age (skewness_age): {skewness_age}")
print(f"Kurtosis of Age (kurtosis_age): {kurtosis_age}")


sns.histplot(race_data, kde=False, color='red', bins=30)
plt.title('Race Distribution of People Killed by Police')
plt.xlabel('Race')
plt.ylabel('Frequency')
plt.show()

race_counts = race_data.value_counts()

# Print the frequency of each race
for race, count in race_counts.items():
    print(f"Race: {race}, Frequency: {count}")

# Age by Race Distribution
for race, ages in ages_by_race.items():
```

```python
    sns.kdeplot(ages, shade=True, label=f'{race} Age Distribution')

# Set plot title and labels
plt.title('Smooth Histogram of Age by Race')
plt.xlabel('Age')
plt.ylabel('Density')
plt.legend()
plt.show()# Filtering data to include entries with both age and race information
filtered_data = dataset.dropna(subset=['age', 'race'])

# Getting unique race categories from the dataset
race_categories = filtered_data['race'].unique()

# Initializing a dictionary to hold age data for each race
ages_by_race = {race: filtered_data[filtered_data['race'] == race]['age'] for race in
race_categories}

# Calculating descriptive statistics for each race
stats_by_race = {}
for race, ages in ages_by_race.items():
    stats_by_race[race] = {
        'Median': ages.median(),
        'Mean': ages.mean(),
        'Standard Deviation': ages.std(),

    }

# Displaying the calculated statistics for each race
stats_by_race

# Monthly and Yearly Distribution

# Assuming you have a DataFrame called 'data' with a 'date' column
data['date'] = pd.to_datetime(data['date'])

# Extract year and month from the 'date' column
data['year'] = data['date'].dt.year
data['month'] = data['date'].dt.month

# Create subplots for yearly and monthly distributions side by side
fig, axes = plt.subplots(1, 2, figsize=(16, 6))

# Yearly Distribution
yearly_counts = data['year'].value_counts().sort_index()
yearly_colors = sns.color_palette("Blues", len(yearly_counts))
sns.barplot(x=yearly_counts.index, y=yearly_counts.values, palette=yearly_colors,
ax=axes[0])
axes[0].set_title('Yearly Distribution of Shootings')
```

```
axes[0].set_xlabel('Year')
axes[0].set_ylabel('Frequency')

# Print yearly counts
print("Yearly Distribution:")
for year, count in yearly_counts.items():
    print(f"Year: {year}, Frequency: {count}")

# Monthly Distribution
monthly_counts = data['month'].value_counts().sort_index()
monthly_colors = sns.color_palette("Oranges", len(monthly_counts))
sns.barplot(x=monthly_counts.index - 1, y=monthly_counts.values,
palette=monthly_colors, ax=axes[1])
axes[1].set_title('Monthly Distribution of Shootings')
axes[1].set_xlabel('Month')
axes[1].set_ylabel('Frequency')

# Set the x-axis labels to month names
axes[1].set_xticks(range(12))  # Set the ticks from 0 to 11 (for each month)
axes[1].set_xticklabels([calendar.month_abbr[i] for i in range(1, 13)])  # Set month
names as labels

# Print monthly counts
print("\nMonthly Distribution:")
for month, count in monthly_counts.items():
    print(f"Month: {calendar.month_abbr[month]}, Frequency: {count}")

plt.tight_layout()
plt.show()

# Gender Distribution
fig, ax = plt.subplots(figsize=(8, 6))
data = dataset.dropna(subset=['latitude', 'longitude','signs_of_mental_illness',
'gender', 'race', 'flee', 'body_camera','armed','threat_level'])
gender_counts = data['gender'].value_counts()
gender_colors = sns.color_palette("Set2", len(gender_counts))
sns.barplot(x=gender_counts.index, y=gender_counts.values, palette=gender_colors,
ax=ax)
ax.set_title('Gender Distribution of People Killed by Police')
ax.set_xlabel('Gender')
ax.set_ylabel('Frequency')

plt.tight_layout()
plt.show()

# Print gender counts
print("Gender Distribution:")
for gender, count in gender_counts.items():
```

```
    print(f"Gender: {gender}, Frequency: {count}")

# State-wise and City -wise distribution
state_counts = data['state'].value_counts()
city_counts = data['city'].value_counts().head(20)

# Create subplots for state-wise and city-wise distributions side by side
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(16, 6))
state_colors = sns.color_palette("Set2", len(state_counts))
city_colors = sns.color_palette("Set2", len(city_counts))

# State-wise Distribution Plot


# Create a subplot for state-wise distribution
fig, ax = plt.subplots(figsize=(14, 8))
state_colors = sns.color_palette("Set2", len(state_counts))
sns.barplot(x=state_counts.values, y=state_counts.index, palette=state_colors, ax=ax)
ax.set_title('State-wise Distribution of Shootings (All States)')
ax.set_xlabel('Frequency')
ax.set_ylabel('State')

# Print state-wise counts (All States) within the bars
print("State-wise Distribution (All States):")
for i, (state, count) in enumerate(state_counts.items()):
    ax.text(count, i, f" {count} ", va='center', fontsize=12, color='black')

# Print state-wise counts (Top 20) within the bars


# City-wise Distribution Plot
sns.barplot(x=city_counts.values, y=city_counts.index, palette=city_colors, ax=ax2)
ax2.set_title('City-wise Distribution of Shootings (Top 20)')
ax2.set_xlabel('Frequency')
ax2.set_ylabel('City')

# Print city-wise counts (Top 20) within the bars
print("\nCity-wise Distribution (Top 20):")
for i, (city, count) in enumerate(city_counts.items()):
    ax2.text(count, i, f" {count} ", va='center', fontsize=12, color='black')

plt.tight_layout()
plt.show()

# Threat level, fleeing and body camera Distribution

# Create a figure with subplots
fig, axs = plt.subplots(1, 3, figsize=(15, 5))
```

```python
threat_level_counts = df['threat_level'].value_counts()
flee_counts = df['flee'].value_counts()
body_camera_counts = df['body_camera'].value_counts()

# Plot threat level bar graph
axs[0].bar(df['threat_level'].value_counts().index, df['threat_level'].value_counts(),
color='skyblue')
axs[0].set_title('Threat Level Distribution')
axs[0].set_xlabel('Threat Level')
axs[0].set_ylabel('Count')
axs[0].tick_params(axis='x', rotation=45)

# Plot fleeing bar graph
axs[1].bar(df['flee'].value_counts().index, df['flee'].value_counts(),
color='lightcoral')
axs[1].set_title('Fleeing Distribution')
axs[1].set_xlabel('Fleeing Status')
axs[1].set_ylabel('Count')
axs[1].tick_params(axis='x', rotation=45)

# Plot body camera presence bar graph
axs[2].bar(df['body_camera'].value_counts().index, df['body_camera'].value_counts(),
color='lightgreen')
axs[2].set_title('Body Camera Presence Distribution')
axs[2].set_xlabel('Body Camera')
axs[2].set_ylabel('Count')
plt.xticks(range(2), ['True', 'False'], rotation=0)

# Adjust spacing between subplots
plt.tight_layout()

# Show the combined plot
plt.show()

print("Threat Level Distribution:")
print(threat_level_counts)
print()

# Print counts for fleeing
print("Fleeing Distribution:")
print(flee_counts)
print()

# Print counts for body camera presence
print("Body Camera Presence Distribution:")
print(body_camera_counts)
```

```python
# K-Means Clustering

# Load your dataset
df = pd.read_excel("/Users/tysonmukesh/Desktop/MTH-522/Project-2/Shootings.xls")
# Remove rows with NaN values in 'latitude' or 'longitude' columns
df = df.dropna(subset=['latitude', 'longitude'])

# Extract latitude and longitude columns
Lat = df['latitude'].values
Lon = df['longitude'].values

# Create a NumPy array of coordinates
geo = np.array([[Lat[i], Lon[i]] for i in range(len(Lat))])

# Specify the number of clusters (you can change this as needed)
num_clusters = 10

# Use K-Means clustering
kmeans = KMeans(n_clusters=num_clusters, random_state=0)
labels = kmeans.fit_predict(geo)

# Print the number of clusters
print(f"Number of clusters in  K-Means Clustering: {num_clusters}")

# Print the total data points taken
total_data_points = len(geo)
print(f"Total data points taken: {total_data_points}")

# Create an empty list to store clusters
clusters = []

# Assign points to the appropriate cluster in the list
for cluster_num in range(num_clusters):
    cluster_points = geo[labels == cluster_num]
    clusters.append(cluster_points.tolist())

    # Print the total number of elements in each cluster
    num_elements_in_cluster = len(cluster_points)
    print(f"Total elements in Cluster {cluster_num}: {num_elements_in_cluster}")

    # Print the elements present in each cluster side by side


# Create a folium map
m = folium.Map(location=[np.mean(Lat), np.mean(Lon)], zoom_start=6)

# Define colors for clusters
colors = ['red', 'blue', 'darkgreen', 'purple', 'orange', 'darkred',
```

```python
          'violet', 'pink', 'yellow','black']

# Plot the clustered points on the map
for idx, cluster in enumerate(clusters):
    color = colors[idx % len(colors)]
    for point in cluster:
        folium.CircleMarker(
            location=point,
            radius=1,  # Reduce the radius to 2 (or any desired value)
            color=color,
            fill=True,
            fill_color=color
        ).add_to(m)

# Display the map
m

# DBSCAN Clustering

# Load your dataset
df = pd.read_excel("/Users/tysonmukesh/Desktop/MTH-522/Project-2/Shootings.xls")
# Remove rows with NaN values in 'latitude' or 'longitude' columns
df = df.dropna(subset=['latitude', 'longitude'])

# Extract latitude and longitude columns
Lat = df['latitude'].values
Lon = df['longitude'].values

# Create a NumPy array of coordinates
geo = np.array([[Lat[i], Lon[i]] for i in range(len(Lat))])

# Initialize DBSCAN with parameters (you can adjust these as needed)
epsilon = 0.5  # Radius for neighborhood
min_samples = 5  # Minimum number of samples in a neighborhood

dbscan = DBSCAN(eps=epsilon, min_samples=min_samples)
labels = dbscan.fit_predict(geo)

# Find the number of clusters (-1 represents noise points)
num_clusters = len(set(labels)) - (1 if -1 in labels else 0)
print(f"Number of clusters in DBSCAN Clustering: {num_clusters}")

# Create an empty list to store clusters
clusters = []

# Assign points to the appropriate cluster in the list
for cluster_num in range(num_clusters):
    cluster_points = geo[labels == cluster_num]
```

```
    clusters.append(cluster_points.tolist())

# Create a folium map
m = folium.Map(location=[np.mean(Lat), np.mean(Lon)], zoom_start=6)

# Define colors for clusters
colors = ['red', 'blue', 'darkgreen', 'purple', 'orange', 'darkred',
          'violet', 'pink', 'yellow', 'black']

# Plot the clustered points on the map
for idx, cluster in enumerate(clusters):
    color = colors[idx % len(colors)]
    for point in cluster:
        folium.CircleMarker(
            location=point,
            radius=1,  # Reduce the radius to 2 (or any desired value)
            color=color,
            fill=True,
            fill_color=color
        ).add_to(m)

# Display the map
m

# K-Medoids Clustering

# Load your dataset
df = pd.read_excel("/Users/tysonmukesh/Desktop/MTH-522/Project-2/Shootings.xls")
# Remove rows with NaN values in 'latitude' or 'longitude' columns
df = df.dropna(subset=['latitude', 'longitude'])

# Extract latitude and longitude columns
Lat = df['latitude'].values
Lon = df['longitude'].values

# Create a NumPy array of coordinates
geo = np.array([[Lat[i], Lon[i]] for i in range(len(Lat))])

# Specify the number of clusters (you can change this as needed)
num_clusters = 10

# Randomly initialize medoids
initial_medoids = np.random.choice(len(geo), num_clusters, replace=False)
medoids = geo[initial_medoids]

# Maximum number of iterations
max_iterations = 100
```

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# Perform K-Medoids clustering
for _ in range(max_iterations):
    # Assign each point to the nearest medoid
    labels = np.argmin(np.linalg.norm(geo[:, np.newaxis] - medoids, axis=2), axis=1)

    # Update medoids by selecting the point with the minimum total distance to others
in its cluster
    new_medoids = np.array([geo[labels == i].mean(axis=0) for i in
range(num_clusters)])

    # Check for convergence
    if np.all(medoids == new_medoids):
        break

    medoids = new_medoids

# Print the number of clusters
print(f"Number of clusters K-Medoids: {num_clusters}")

# Create an empty list to store clusters
clusters = []

# Assign points to the appropriate cluster in the list
for cluster_num in range(num_clusters):
    cluster_points = geo[labels == cluster_num]
    clusters.append(cluster_points.tolist())

# Create a folium map
m = folium.Map(location=[np.mean(Lat), np.mean(Lon)], zoom_start=6)

# Define colors for clusters
colors = ['red', 'blue', 'darkgreen', 'purple', 'orange', 'darkred',
          'violet', 'pink', 'yellow', 'black']

# Plot the clustered points on the map
for idx, cluster in enumerate(clusters):
    color = colors[idx % len(colors)]
    for point in cluster:
        folium.CircleMarker(
            location=point,
            radius=1,  # Reduce the radius to 2 (or any desired value)
            color=color,
            fill=True,
            fill_color=color
        ).add_to(m)

# Display the map
m
```

Contributions:

- **Mukesh Kumar Karanam Rameshbabu –** Worked on Findings, coding, Discussions, Methods and Results.
- **Sai Sudhamsh Kamisetty –** Worked on issues, coding, graphs and results.
- **Rohith Rasi Reddy –** Worked on initial cleaning of data using excel and coding.
- **Anish Krishna Kalisetti –** Worked on results and report preparation.