

ata-analysis-on-gun-violence-in-us

November 15, 2024

1 Data Analysis on Gun Violence in US

1.0.1 About Dataset

- Gun Violence Dataset Overview (Mass Shootings in 2024)
- This dataset provides an in-depth look at mass shootings across the United States in 2024, up until October 20th, sourced from the Gun Violence Archive.
- It captures essential details such as incident ID, date, state, city, victims (killed and injured), and suspects involved.
- Additionally, geographical coordinates are included to allow for spatial analysis of gun violence trends.

1.0.2 Key Features of the Dataset

- Incident IDs: A unique identifier for each incident, categorized and grouped based on their range.
- Incident Date: Captures the time period over which the incidents occurred, broken down into monthly intervals.
- State and City/County: A breakdown of incidents across various states and cities, identifying regions with the most gun violence activity.
- Victims Killed and Injured: Provides a count of victims in each incident, allowing for the analysis of both fatal and non-fatal outcomes.
- Suspects Killed, Injured, and Arrested: Captures data related to suspects involved in the incidents, including their status post-incident (e.g., killed, injured, or arrested).
- Latitude and Longitude: Geographical coordinates for the locations of the incidents, enabling mapping and geospatial analysis.
- Coordinates Found: Indicates whether valid geographical coordinates were found for each incident.

```
[1]: #Loading Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
[2]: #loading dataset
df = pd.read_csv("Dataset/gun.csv")
```

```
[3]: df.head()
```

```
[3]:
```

	Incident ID	Incident Date	State	City Or County	\
0	3052758	October 21, 2024	Washington	Fall City	
1	3052028	October 20, 2024	Tennessee	Jackson	
2	3051984	October 20, 2024	Louisiana	Baton Rouge	
3	3051041	October 19, 2024	Pennsylvania	Philadelphia	
4	3050940	October 19, 2024	Mississippi	Lexington	

	Address	Victims Killed	Victims Injured	\
0	7700 block of Lake Alice Rd SE	5	1	
1	2310 N Highland Ave	1	8	
2	9700 block of Greenwell Springs Rd	0	5	
3	2517 N Jessup St	0	7	
4	24904 MS-17	3	8	

	Suspects Killed	Suspects Injured	Suspects Arrested	Operations	Latitude	\
0	0	0	1	NaN	47.56812	
1	0	0	0	NaN	35.61390	
2	0	0	0	NaN	30.44335	
3	0	0	0	NaN	39.95222	
4	0	0	0	NaN	33.11464	

	Longitude	Coordinates_Found
0	-121.89086	Yes
1	-88.81940	Yes
2	-91.18664	Yes
3	-75.16218	Yes
4	-90.05281	Yes

```
[4]: df.columns
```

```
[4]: Index(['Incident ID', 'Incident Date', 'State', 'City Or County', 'Address',  
        'Victims Killed', 'Victims Injured', 'Suspects Killed',  
        'Suspects Injured', 'Suspects Arrested', 'Operations', 'Latitude',  
        'Longitude', 'Coordinates_Found'],  
        dtype='object')
```

```
[5]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>  
RangeIndex: 427 entries, 0 to 426  
Data columns (total 14 columns):  
#   Column                Non-Null Count  Dtype  
---  -  
0   Incident ID           427 non-null    int64  
1   Incident Date         427 non-null    object
```

```

2   State                427 non-null    object
3   City Or County       427 non-null    object
4   Address              426 non-null    object
5   Victims Killed       427 non-null    int64
6   Victims Injured     427 non-null    int64
7   Suspects Killed      427 non-null    int64
8   Suspects Injured    427 non-null    int64
9   Suspects Arrested   427 non-null    int64
10  Operations           0 non-null     float64
11  Latitude             427 non-null    float64
12  Longitude            427 non-null    float64
13  Coordinates_Found   427 non-null    object
dtypes: float64(3), int64(6), object(5)
memory usage: 46.8+ KB

```

```
[6]: df.describe()
```

```

[6]:      Incident ID  Victims Killed  Victims Injured  Suspects Killed  \
count  4.270000e+02      427.000000      427.000000      427.000000
mean    2.929432e+06      1.000000      4.437939      0.070258
std     6.876031e+04      1.210285      2.849555      0.264896
min     2.791411e+06      0.000000      0.000000      0.000000
25%     2.879320e+06      0.000000      3.000000      0.000000
50%     2.939030e+06      1.000000      4.000000      0.000000
75%     2.982807e+06      1.000000      5.000000      0.000000
max     3.052758e+06      8.000000     28.000000      2.000000

      Suspects Injured  Suspects Arrested  Operations  Latitude  Longitude
count      427.000000      427.000000      0.0  427.000000  427.000000
mean         0.063232      0.711944      NaN   36.941819  -88.791959
std          0.271030      1.178414      NaN    4.934289   12.976850
min           0.000000      0.000000      NaN   21.449910 -166.739450
25%           0.000000      0.000000      NaN   33.449545  -91.910580
50%           0.000000      0.000000      NaN   37.687490  -86.811790
75%           0.000000      1.000000      NaN   40.692450  -80.735325
max           2.000000      7.000000      NaN   68.349440  -70.256650

```

```
[8]: df.isna().sum()
```

```

[8]: Incident ID      0
     Incident Date    0
     State           0
     City Or County   0
     Address          1
     Victims Killed    0
     Victims Injured   0
     Suspects Killed   0

```

```

Suspects Injured      0
Suspects Arrested     0
Operations            427
Latitude              0
Longitude             0
Coordinates_Found     0
dtype: int64

```

```
[9]: df.shape
```

```
[9]: (427, 14)
```

```
[12]: df.drop(df[['Address','Operations']], axis=1,inplace=True)
```

```
[13]: df.head()
```

```
[13]:
```

	Incident ID	Incident Date	State	City Or County	Victims Killed \
0	3052758	October 21, 2024	Washington	Fall City	5
1	3052028	October 20, 2024	Tennessee	Jackson	1
2	3051984	October 20, 2024	Louisiana	Baton Rouge	0
3	3051041	October 19, 2024	Pennsylvania	Philadelphia	0
4	3050940	October 19, 2024	Mississippi	Lexington	3

	Victims Injured	Suspects Killed	Suspects Injured	Suspects Arrested \
0	1	0	0	1
1	8	0	0	0
2	5	0	0	0
3	7	0	0	0
4	8	0	0	0

	Latitude	Longitude	Coordinates_Found
0	47.56812	-121.89086	Yes
1	35.61390	-88.81940	Yes
2	30.44335	-91.18664	Yes
3	39.95222	-75.16218	Yes
4	33.11464	-90.05281	Yes

```
[15]: df.isna().sum()
```

```
[15]:
```

Incident ID	0
Incident Date	0
State	0
City Or County	0
Victims Killed	0
Victims Injured	0
Suspects Killed	0
Suspects Injured	0

```
Suspects Arrested    0
Latitude             0
Longitude            0
Coordinates_Found    0
dtype: int64
```

```
[16]: df.shape
```

```
[16]: (427, 12)
```

1. What is the total number of incidents in the dataset?

```
[17]: total_incidents = df.shape[0]
      print(f"Total number of incidents: {total_incidents}")
```

```
Total number of incidents: 427
```

```
[ ]:
```

2.State with the highest number of incidents

```
[19]: highest_incidents = df['State'].value_counts().idxmax()
      print(f"State with the highest number of incidents: {highest_incidents}")
```

```
State with the highest number of incidents: Illinois
```

```
[ ]:
```

3. Total number of victims killed and injured

```
[23]: total_victims_killed = df['Victims Killed'].sum()
      total_victims_injured = df['Victims Injured'].sum()
      print(f"Total victims killed: {total_victims_killed},\nTotal victims injured: \n{total_victims_injured}")
```

```
Total victims killed: 427,
Total victims injured: 1895
```

```
[ ]:
```

4. Average number of suspects arrested per incident

```
[24]: average_suspects_arrested = df['Suspects Arrested'].mean()
      print(f"Average suspects arrested per incident: {average_suspects_arrested:.2f}")
```

```
Average suspects arrested per incident: 0.71
```

```
[ ]:
```

5. Number of incidents by year

```
[26]: df['Incident Year'] = pd.to_datetime(df['Incident Date']).dt.year
      incidents_by_year = df['Incident Year'].value_counts()
      print("Number of incidents by year: ")
      print(incidents_by_year)
```

```
Number of incidents by year:
2024      427
Name: Incident Year, dtype: int64
```

```
[ ]:
```

6. Coordinates of the incident with the highest total victims (killed + injured)

```
[27]: df['Total Victims'] = df['Victims Killed'] + df['Victims Injured']
      most_affected_coordinates = df.loc[df['Total Victims'].idxmax(), ['Latitude', 'Longitude']]
      print("Coordinates of the most affected incident:")
      print(most_affected_coordinates)
```

```
Coordinates of the most affected incident:
Latitude      41.08431
Longitude     -81.51431
Name: 233, dtype: object
```

```
[ ]:
```

1.1 Data Visualization using Mayavi and python

```
[ ]:
```

```
[29]: !pip install mayavi
```

```
Collecting mayavi
  Downloading mayavi-4.8.2.tar.gz (7.1 MB)
----- 0.0/7.1 MB ? eta -:--:--
----- 0.0/7.1 MB 682.7 kB/s eta 0:00:11
- ----- 0.3/7.1 MB 3.5 MB/s eta 0:00:02
----- 1.5/7.1 MB 11.0 MB/s eta 0:00:01
----- 2.8/7.1 MB 16.0 MB/s eta 0:00:01
----- 3.2/7.1 MB 14.7 MB/s eta 0:00:01
----- 4.4/7.1 MB 15.5 MB/s eta 0:00:01
----- 5.2/7.1 MB 16.5 MB/s eta 0:00:01
----- 6.3/7.1 MB 17.5 MB/s eta 0:00:01
----- 7.1/7.1 MB 17.5 MB/s eta 0:00:00

Installing build dependencies: started
Installing build dependencies: finished with status 'done'
```

```

Getting requirements to build wheel: started
Getting requirements to build wheel: finished with status 'done'
Preparing metadata (pyproject.toml): started
Preparing metadata (pyproject.toml): finished with status 'done'
Collecting apptools (from mayavi)
  Downloading apptools-5.3.0-py3-none-any.whl.metadata (4.3 kB)
Collecting envisage (from mayavi)
  Downloading envisage-7.0.3-py3-none-any.whl.metadata (5.2 kB)
Requirement already satisfied: numpy in c:\users\user\anaconda3\lib\site-packages (from mayavi) (1.24.4)
Collecting pyface>=6.1.1 (from mayavi)
  Downloading pyface-8.0.0-py3-none-any.whl.metadata (7.7 kB)
Requirement already satisfied: pygments in c:\users\user\anaconda3\lib\site-packages (from mayavi) (2.15.1)
Collecting traits>=6.0.0 (from mayavi)
  Downloading traits-6.4.3-cp311-cp311-win_amd64.whl.metadata (5.2 kB)
Collecting traitsui>=7.0.0 (from mayavi)
  Downloading traitsui-8.0.0-py3-none-any.whl.metadata (6.8 kB)
Requirement already satisfied: packaging in c:\users\user\anaconda3\lib\site-packages (from mayavi) (23.1)
Collecting vtk (from mayavi)
  Using cached vtk-9.3.1-cp311-cp311-win_amd64.whl.metadata (5.3 kB)
Requirement already satisfied: setuptools in c:\users\user\anaconda3\lib\site-packages (from envisage->mayavi) (68.2.2)
Requirement already satisfied: matplotlib>=2.0.0 in
c:\users\user\anaconda3\lib\site-packages (from vtk->mayavi) (3.8.0)
Requirement already satisfied: contourpy>=1.0.1 in
c:\users\user\anaconda3\lib\site-packages (from matplotlib>=2.0.0->vtk->mayavi)
(1.2.0)
Requirement already satisfied: cyclical>=0.10 in c:\users\user\anaconda3\lib\site-packages (from matplotlib>=2.0.0->vtk->mayavi) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
c:\users\user\anaconda3\lib\site-packages (from matplotlib>=2.0.0->vtk->mayavi)
(4.25.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
c:\users\user\anaconda3\lib\site-packages (from matplotlib>=2.0.0->vtk->mayavi)
(1.4.4)
Requirement already satisfied: pillow>=6.2.0 in
c:\users\user\anaconda3\lib\site-packages (from matplotlib>=2.0.0->vtk->mayavi)
(10.2.0)
Requirement already satisfied: pyparsing>=2.3.1 in
c:\users\user\anaconda3\lib\site-packages (from matplotlib>=2.0.0->vtk->mayavi)
(3.0.9)
Requirement already satisfied: python-dateutil>=2.7 in
c:\users\user\anaconda3\lib\site-packages (from matplotlib>=2.0.0->vtk->mayavi)
(2.8.2)
Requirement already satisfied: six>=1.5 in c:\users\user\anaconda3\lib\site-packages (from python-dateutil>=2.7->matplotlib>=2.0.0->vtk->mayavi) (1.16.0)

```

```

Downloading pyface-8.0.0-py3-none-any.whl (1.3 MB)
----- 0.0/1.3 MB ? eta -:--:--
----- 1.0/1.3 MB 31.4 MB/s eta 0:00:01
----- 1.3/1.3 MB 16.6 MB/s eta 0:00:00
Downloading traits-6.4.3-cp311-cp311-win_amd64.whl (5.0 MB)
----- 0.0/5.0 MB ? eta -:--:--
----- 1.1/5.0 MB 34.6 MB/s eta 0:00:01
----- 1.4/5.0 MB 17.9 MB/s eta 0:00:01
----- 2.2/5.0 MB 17.7 MB/s eta 0:00:01
----- 3.7/5.0 MB 21.5 MB/s eta 0:00:01
----- 5.0/5.0 MB 22.8 MB/s eta 0:00:01
----- 5.0/5.0 MB 21.3 MB/s eta 0:00:00
Downloading traitsui-8.0.0-py3-none-any.whl (1.5 MB)
----- 0.0/1.5 MB ? eta -:--:--
----- 1.1/1.5 MB 22.7 MB/s eta 0:00:01
----- 1.5/1.5 MB 24.4 MB/s eta 0:00:00
Downloading apptools-5.3.0-py3-none-any.whl (230 kB)
----- 0.0/230.0 kB ? eta -:--:--
----- 230.0/230.0 kB 13.7 MB/s eta 0:00:00
Downloading envisage-7.0.3-py3-none-any.whl (268 kB)
----- 0.0/268.9 kB ? eta -:--:--
----- 268.9/268.9 kB ? eta 0:00:00
Using cached vtk-9.3.1-cp311-cp311-win_amd64.whl (52.5 MB)
Building wheels for collected packages: mayavi
  Building wheel for mayavi (pyproject.toml): started
  Building wheel for mayavi (pyproject.toml): still running...
  Building wheel for mayavi (pyproject.toml): finished with status 'done'
  Created wheel for mayavi: filename=mayavi-4.8.2-py3-none-any.whl size=19034131
  sha256=c778decf85c34c2fffa4294d97faf91d3f931a31a2b05dfef338b57a55b6bb2b
  Stored in directory: c:\users\user\appdata\local\pip\cache\wheels\c7\57\c0\4ed
  3e25a0d8c0f07072c4d6355cf4639945a8bf88afaf67558
Successfully built mayavi
Installing collected packages: traits, pyface, apptools, vtk, traitsui,
envisage, mayavi
Successfully installed apptools-5.3.0 envisage-7.0.3 mayavi-4.8.2 pyface-8.0.0
traits-6.4.3 traitsui-8.0.0 vtk-9.3.1

```

```
[31]: !pip install configobj
```

```

Collecting configobj
  Downloading configobj-5.0.9.tar.gz (101 kB)
----- 0.0/101.5 kB ? eta -:--:--
----- 10.2/101.5 kB ? eta -:--:--
----- 92.2/101.5 kB 1.3 MB/s eta 0:00:01
----- 101.5/101.5 kB 981.5 kB/s eta 0:00:00
Installing build dependencies: started
Installing build dependencies: finished with status 'done'
Getting requirements to build wheel: started

```



```

Getting requirements to build wheel: finished with status 'done'
Preparing metadata (pyproject.toml): started
Preparing metadata (pyproject.toml): finished with status 'done'
Building wheels for collected packages: configobj
Building wheel for configobj (pyproject.toml): started
Building wheel for configobj (pyproject.toml): finished with status 'done'
Created wheel for configobj: filename=configobj-5.0.9-py2.py3-none-any.whl
size=35637
sha256=7a3d079eb3b69ee73d7ca275a5d3ea154758fed8ca333d91f5c07b2207a93878
Stored in directory: c:\users\user\appdata\local\pip\cache\wheels\64\0b\d9\934
7fb191ffdc88f4b0146338d157b9616de47ddfd93cd2481
Successfully built configobj
Installing collected packages: configobj
Successfully installed configobj-5.0.9

```

```

[32]: from mayavi import mlab
      # Geospatial Heatmap
      latitudes = df['Latitude']
      longitudes = df['Longitude']
      victim_counts = df['Victims Killed'] + df['Victims Injured']

      # 3D Scatter plot
      mlab.figure(size=(800, 600))
      mlab.points3d(latitudes, longitudes, victim_counts,
                    victim_counts,
                    scale_mode='none',
                    scale_factor=10,
                    colormap='coolwarm')
      mlab.axes(xlabel='Latitude', ylabel='Longitude', zlabel='Victim Counts')
      mlab.title("Geospatial Heatmap of Incidents")
      mlab.show()

```

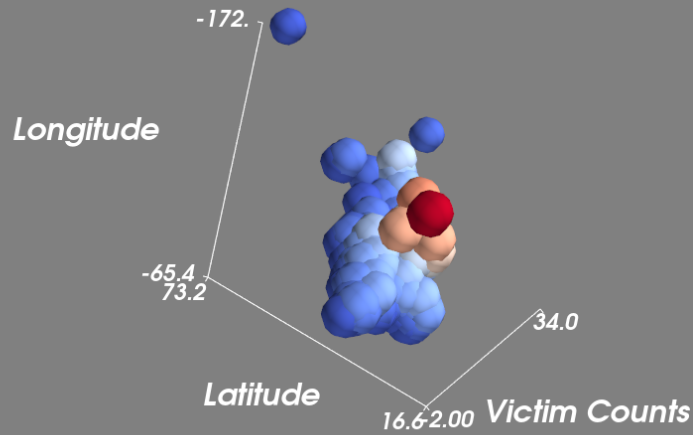
```

[39]: from IPython.display import Image, display

      # Display an image
      image_path = "Images\Geospatial Output.png"
      display(Image(filename=image_path))

```

Geospatial Heatmap of Incidents



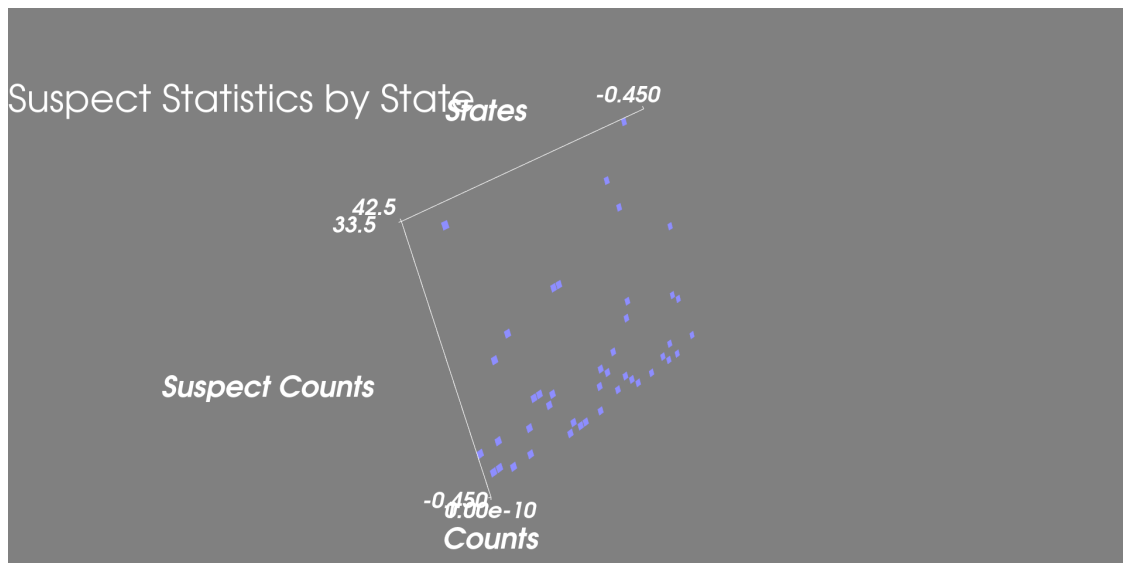
[]:

```
[41]: # Suspect Statistics
states = df['State'].unique()
suspect_counts = df.groupby('State')['Suspects Arrested'].sum()

x = np.arange(len(states))
y = suspect_counts.values

mlab.figure(size=(800, 600))
mlab.barchart(x, y, np.zeros_like(y), colormap='cool', color=(0.5, 0.5, 1.0))
mlab.axes(xlabel='States', ylabel='Suspect Counts', zlabel='Counts')
mlab.title("Suspect Statistics by State")
mlab.show()
```

```
[40]: # Display an image
image_path = "Images\Suspect Output.png" # Replace with your image path
display(Image(filename=image_path))
```



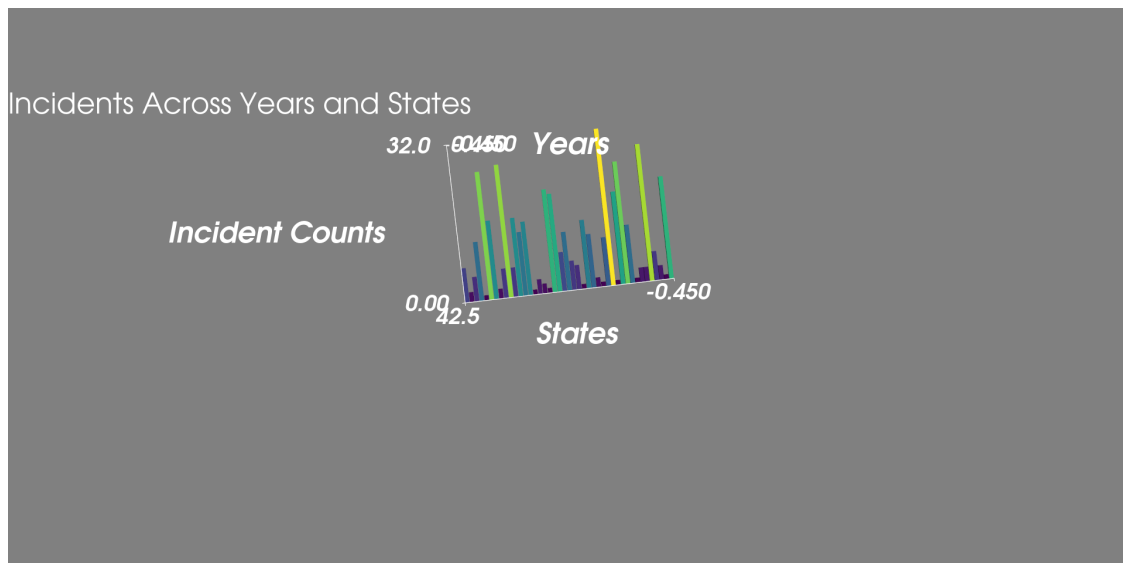
```
[47]: # Temporal Trend

# Data preparation
years = df['Incident Year'].unique()
states = df['State'].unique()
incident_counts = df.groupby(['Incident Year', 'State']).size().
    ↪unstack(fill_value=0)

x, y = np.meshgrid(range(len(years)), range(len(states)))
z = incident_counts.values.T

# 3D Bar plot
mlab.figure(size=(800, 600))
mlab.barchart(x, y, z, colormap='viridis')
mlab.axes(xlabel='Years', ylabel='States', zlabel='Incident Counts')
mlab.title("Incidents Across Years and States")
mlab.show()

[48]: # Display an image
image_path = "Images\incident.png" # Replace with your image path
display(Image(filename=image_path))
```



[]:

[]:

- **Geospatial Clustering of Incidents:** The analysis revealed geographic hotspots where incidents are more frequent, helping identify areas with high criminal activity or risk.
- **Impact Analysis by Location:** Visualizing the number of victims killed, injured, or suspects arrested across different regions provides insights into the severity of incidents in specific areas.
- **Risk Zones Identification:** By creating buffers around key locations, we can identify high-risk zones that require increased attention or resources for intervention.
- **Region-Based Aggregation:** Summarizing incident data by cities, counties, or states helps prioritize areas with the most incidents, guiding law enforcement and resource allocation.
- **Effectiveness of Law Enforcement Operations:** Mapping the operations and arrests in relation to incidents shows the effectiveness of law enforcement in addressing crime in high-density areas.
- **Comparative Analysis of Regions:** Comparing incident rates between neighboring regions helps highlight disparities in crime or emergency incidents, offering a foundation for targeted policies.
- **Enhanced Decision-Making for Policy Makers:** The spatial analysis and visualizations provide valuable insights for policy makers to improve crime prevention strategies and optimize resource distribution.

[]: