Hate Crime Prediction

0. Import Modules

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

In [21]:
```
import os
print(os.getcwd())
```

```
c:\Users\Legion 5 Pro\OneDrive\Documents\CP_Project_V2\source_code
```

You can use the following code in case the venu env doesn't work

- Simply put, just force to use your global environment instead
- `Note` : If you use venu env from our depedencies folder, simply comment the following code below...

In [ ]:
```
# import os
# os.chdir("C:/Users/Legion 5 Pro/OneDrive/Documents/CP_Project_V2")
```

1. Load Dataset

In [23]:
```
df = pd.read_csv('datasets/hate_crime.csv')
df.head()
```

Out[23]:

	incident_id	data_year	ori	pug_agency_name	pub_agency_unit	agency_type_nar
0	43	1991	AR0350100	Pine Bluff	NaN	C
1	44	1991	AR0350100	Pine Bluff	NaN	C
2	45	1991	AR0600300	North Little Rock	NaN	C
3	46	1991	AR0600300	North Little Rock	NaN	C
4	47	1991	AR0670000	Sevier	NaN	Cour

5 rows × 28 columns

In [24]:
```
# Check columns
df.columns
```

Out[24]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

In [25]:
```
df['data_year'].unique()
```

Out[25]:
```
array([1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001,
       2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012,
       2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023])
```

In [26]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253776 entries, 0 to 253775
Data columns (total 28 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   incident_id                     253776 non-null  int64  
 1   data_year                       253776 non-null  int64  
 2   ori                             253776 non-null  object 
 3   pug_agency_name                 253776 non-null  object 
 4   pub_agency_unit                 7595 non-null    object 
 5   agency_type_name                253776 non-null  object 
 6   state_abbr                      253776 non-null  object 
 7   state_name                      253776 non-null  object 
 8   division_name                   253776 non-null  object 
 9   region_name                     253776 non-null  object 
 10  population_group_code           253109 non-null  object 
 11  population_group_description    253109 non-null  object 
 12  incident_date                   253776 non-null  object 
 13  adult_victim_count              82700 non-null   float64
 14  juvenile_victim_count           80063 non-null   float64
 15  total_offender_count            253776 non-null  int64  
 16  adult_offender_count            73219 non-null   float64
 17  juvenile_offender_count         73212 non-null   float64
 18  offender_race                   253776 non-null  object 
 19  offender_ethnicity              253776 non-null  object 
 20  victim_count                    253776 non-null  int64  
 21  offense_name                    253776 non-null  object 
 22  total_individual_victims        248651 non-null  float64
 23  location_name                   253776 non-null  object 
 24  bias_desc                       253776 non-null  object 
 25  victim_types                    253776 non-null  object 
 26  multiple_offense                253776 non-null  object 
 27  multiple_bias                   253776 non-null  object 
dtypes: float64(5), int64(4), object(19)
memory usage: 54.2+ MB
```

In [27]:
```
# Check shape
df.shape
```

Out[27]:
```
(253776, 28)
```

In [28]:
```
# Define custom check missing values (columns on)
def check_missing_columns(df):
    index = 0
    for col in df:
        missing_count = df[col].isna().sum()
        if missing_count > 0:
            index += 1
            print(f"{col}: {missing_count}")
    print(f"\nTotal Missing Columns: {index}")
```

In [29]:
```
check_missing_columns(df)
```

```
pub_agency_unit: 246181
population_group_code: 667
population_group_description: 667
adult_victim_count: 171076
juvenile_victim_count: 173713
adult_offender_count: 180557
juvenile_offender_count: 180564
total_individual_victims: 5125

Total Missing Columns: 8
```

In [30]:
```
df.describe()
```

Out[30]:

	incident_id	data_year	adult_victim_count	juvenile_victim_count	total_offend
count	2.537760e+05	253776.000000	82700.000000	80063.000000	25377
mean	4.045290e+05	2007.711320	0.749456	0.107216	
std	5.626399e+05	9.798864	1.089989	0.499702	
min	2.000000e+00	1991.000000	0.000000	0.000000	
25%	6.347575e+04	1999.000000	0.000000	0.000000	
50%	1.269305e+05	2007.000000	1.000000	0.000000	
75%	1.945972e+05	2017.000000	1.000000	0.000000	
max	1.522894e+06	2023.000000	146.000000	60.000000	9

In [31]:
```
df.columns
```

Out[31]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

2. Explonatory Data Analysis (EDA)

Check data_year

In [32]:
```
df['data_year'].dtype
```

Out[32]:
```
dtype('int64')
```

In [33]:
```
df['data_year'].unique()
```

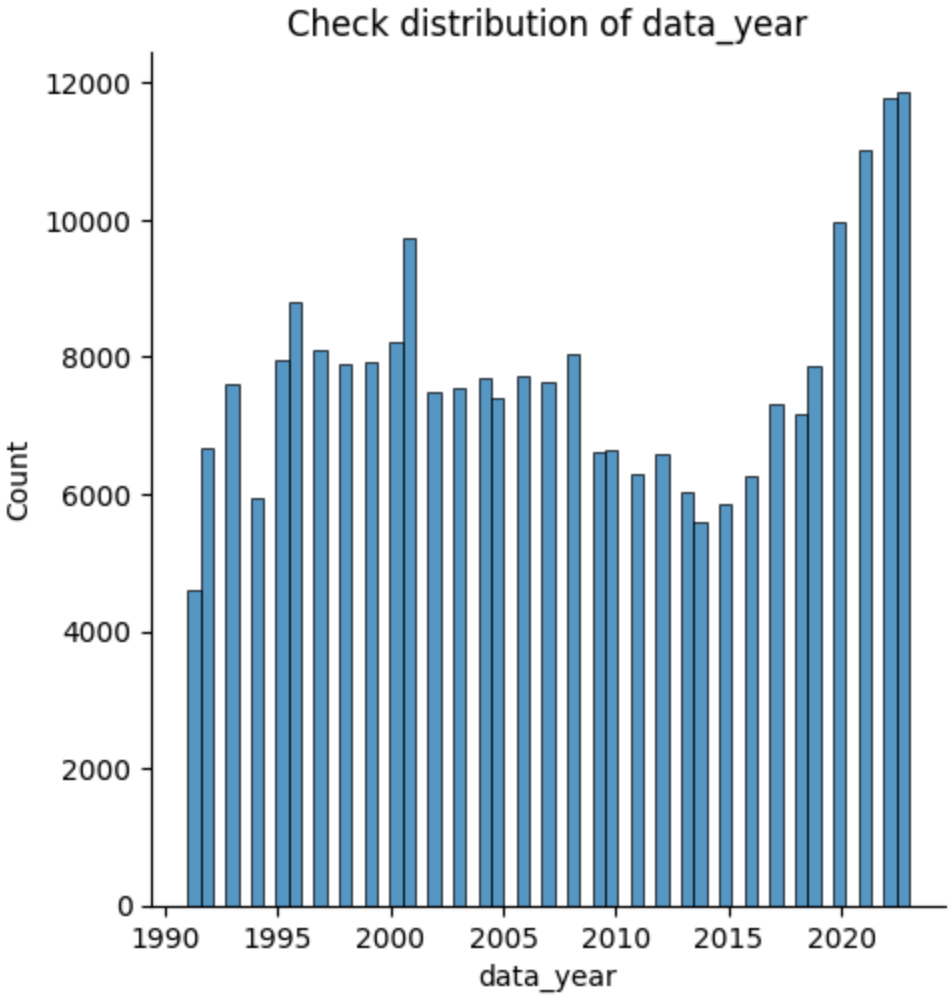
Out[33]:
```
array([1991, 1992, 1993, 1994, 1995, 1996, 1997, 1998, 1999, 2000, 2001,
       2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012,
       2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023])
```

In [34]:
```
df['data_year'].isna().sum()
```

Out[34]:
```
np.int64(0)
```

In [35]:
```
# Check distribution
plt.figure(figsize=(12,7))

sns.displot(df, x='data_year')

plt.title('Check distribution of data_year')
plt.show()

print('Likely skewed to the left: Modern years have higher chance for crime')
```

```
<Figure size 1200x700 with 0 Axes>
```




```
Likely skewed to the left: Modern years have higher chance for crime
```

In [36]:
```
# Check skewness
from scipy.stats import skew

skew_value = skew(df['data_year'])
```

```
print('-'*30)
print(f"Skewness of data_year: {round(skew_value, 4)}")
print('-'*30)
print('The skewness is being around 0.0244 which is very closed to zero')
print('This suggests that the distribution is highly normal')
```

```
------------------------------
Skewness of data_year: 0.0244
------------------------------
The skewness is being around 0.0244 which is very closed to zero
This suggests that the distribution is highly normal
```

In [37]:
```
df.columns
```

Out[37]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

Check ori and state

In [38]:
```
df['ori'].dtype
```

Out[38]:
```
dtype('O')
```

In [39]:
```
df['ori'].unique()
```

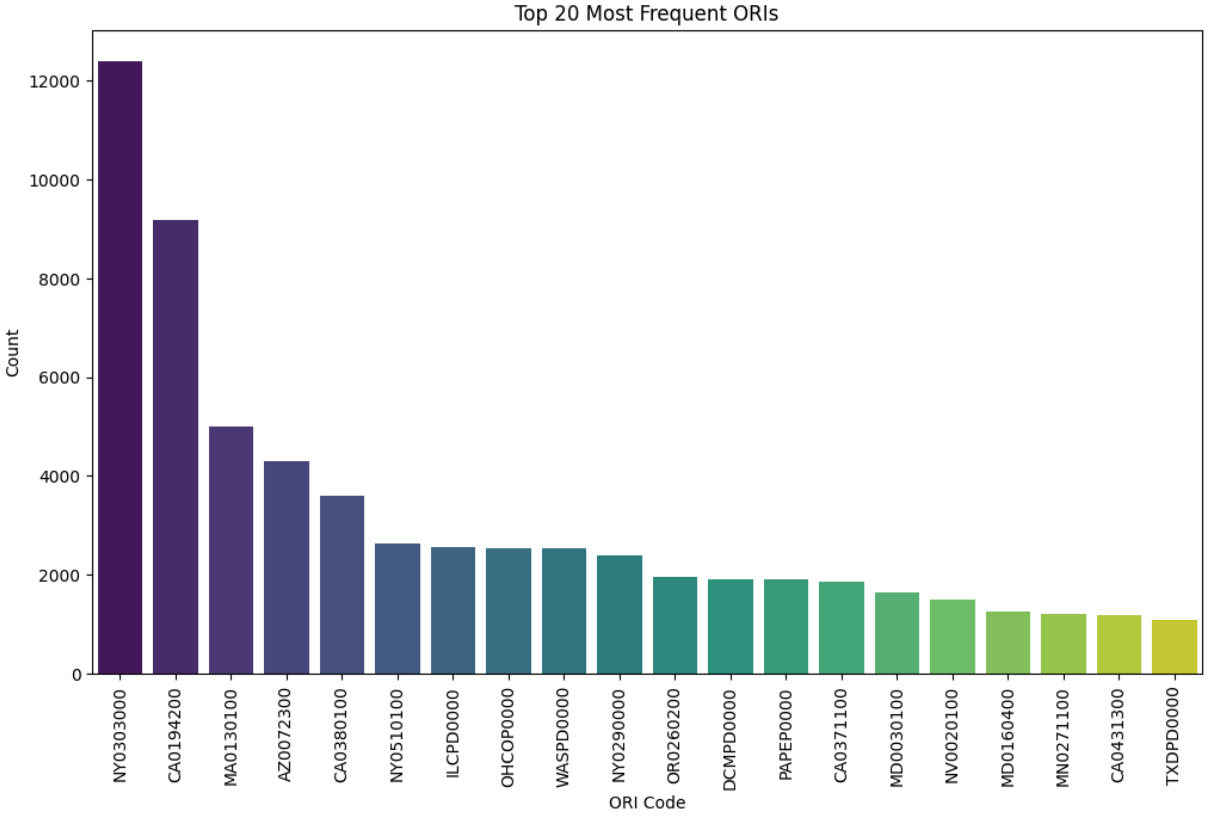
Out[39]:
```
array(['AR0350100', 'AR0600300', 'AR0670000', ..., 'WV0440000',
       'WVWSP1100', 'WY0060300'], shape=(10710,), dtype=object)
```

In [40]:
```
df['ori'].isna().sum()
```

Out[40]:
```
np.int64(0)
```

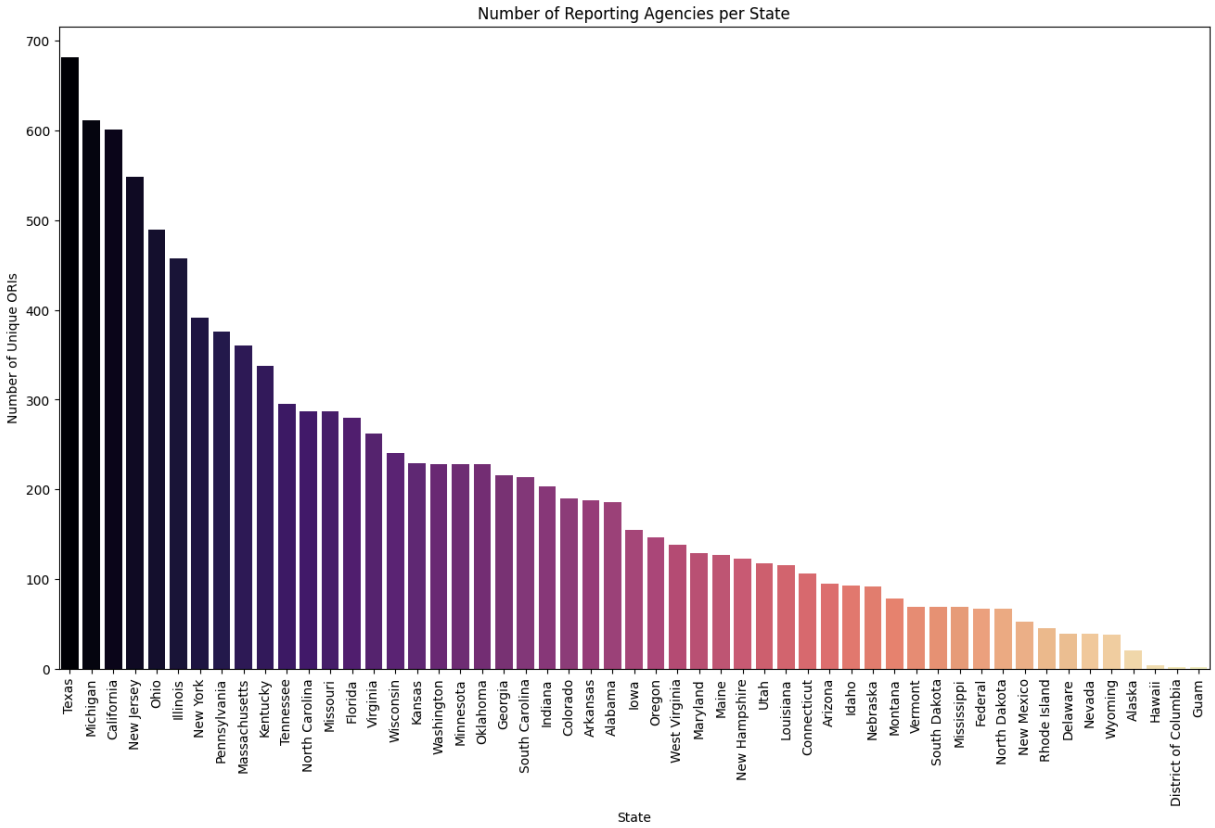
In [41]:
```
# Check distribution
# Count occurrences of each ORI
top_ori = df['ori'].value_counts().head(20)  # Get top 20 most common ORI

# Plot bar chart
plt.figure(figsize=(12, 7))
sns.barplot(x=top_ori.index, y=top_ori.values, palette="viridis")
plt.xticks(rotation=90)
plt.xlabel("ORI Code")
plt.ylabel("Count")
plt.title("Top 20 Most Frequent ORIs")
plt.show()
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\3816221670.py:7: FutureWarni
ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=top_ori.index, y=top_ori.values, palette="viridis")
```



In [42]:
```
# Try grouping ori by state
state_counts = df.groupby("state_name")["ori"].nunique().sort_values(ascending=Fals

plt.figure(figsize=(16, 9))
sns.barplot(x=state_counts.index, y=state_counts.values, palette="magma")
plt.xticks(rotation=90)
plt.xlabel("State")
plt.ylabel("Number of Unique ORIs")
plt.title("Number of Reporting Agencies per State")
plt.show()

print('Larger states with more cities/towns tend to have more ORIs')
print('States with more ORIs tend to have more granular crime reporting, but this d
```

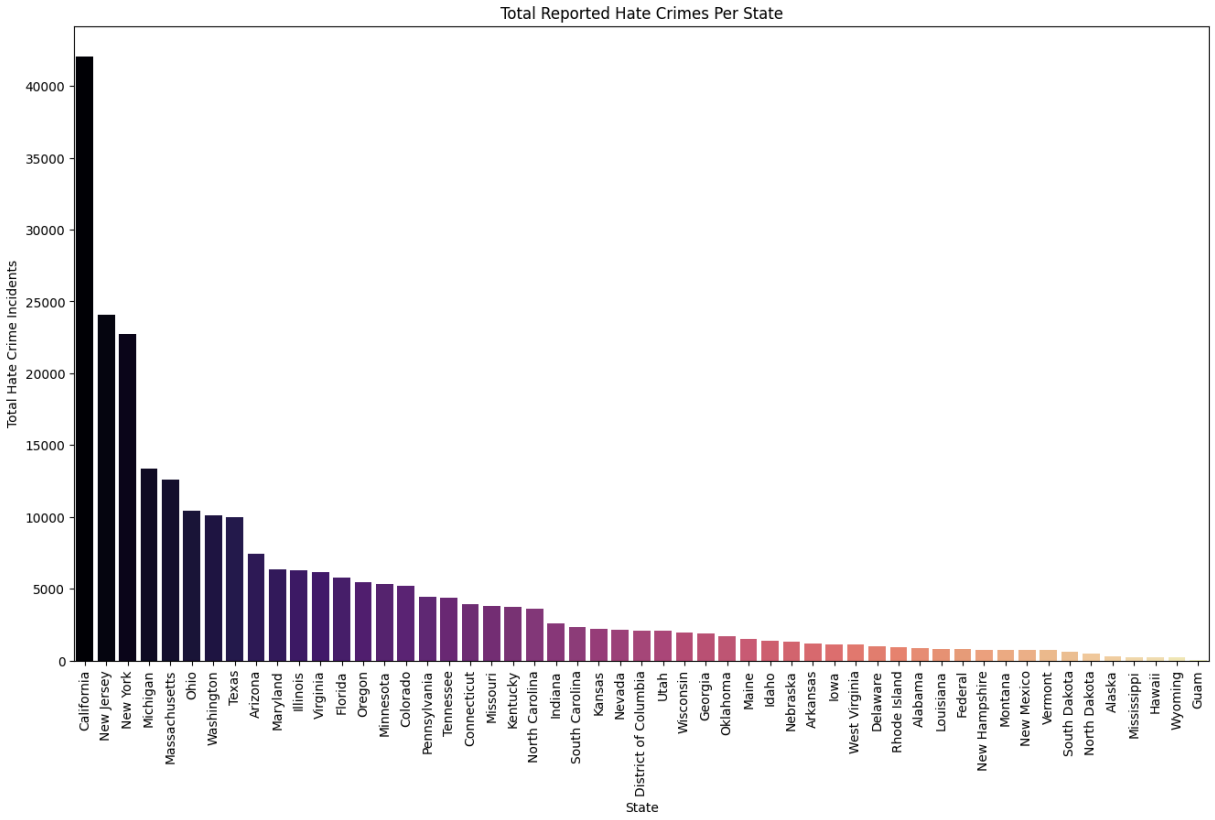
```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\3591222749.py:5: FutureWarni
ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=state_counts.index, y=state_counts.values, palette="magma")
```



Larger states with more cities/towns tend to have more ORIs
States with more ORIs tend to have more granular crime reporting, but this does not mean they have the most crimes.

In [43]:
```
# Check total hate crime per state grouped by total incident
state_crime_counts = df.groupby("state_name")["incident_id"].count().sort_values(as

# Plot
plt.figure(figsize=(16, 9))
sns.barplot(x=state_crime_counts.index, y=state_crime_counts.values, palette="magma
plt.xticks(rotation=90)
plt.xlabel("State")
plt.ylabel("Total Hate Crime Incidents")
plt.title("Total Reported Hate Crimes Per State")
plt.show()

print('California has the most crime detected.')
print('California is the most populous state in the U.S., so it might have more rep
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\3665486666.py:6: FutureWarni
ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=state_crime_counts.index, y=state_crime_counts.values, palette="magm
a")
```



California has the most crime detected.
California is the most populous state in the U.S., so it might have more reported cr
imes overall.

In [44]:
```
# Count crime types per state
crime_types = df.groupby(["state_name", "offense_name"])["incident_id"].count().res

# Get top crime types
top_crime_types = crime_types.sort_values(by="incident_id", ascending=False).groupb


print('Most common hate crime type in California → "Destruction/Damage/Vandalism of
print('Destruction/Vandalism is dominant in multiple states (California, New York,
top_crime_types  # Show the most common hate crime type in each state
```

Most common hate crime type in California → "Destruction/Damage/Vandalism of Propert
y" (12,598 cases!)
Destruction/Vandalism is dominant in multiple states (California, New York, Marylan
d, Texas, Virginia, etc.).

Out[44]:

	state_name	offense_name	incident_id
239	California	Destruction/Damage/Vandalism of Property	12598
1772	New Jersey	Intimidation	12475
1856	New York	Destruction/Damage/Vandalism of Property	9690
1380	Michigan	Intimidation	4349
1267	Massachusetts	Intimidation	4192
1166	Maryland	Destruction/Damage/Vandalism of Property	3634
2098	Ohio	Intimidation	3619
2927	Washington	Intimidation	3466
2571	Texas	Destruction/Damage/Vandalism of Property	2508
2791	Virginia	Destruction/Damage/Vandalism of Property	2444
106	Arizona	Intimidation	2165
561	Florida	Destruction/Damage/Vandalism of Property	1796
1454	Minnesota	Intimidation	1774
771	Illinois	Simple Assault	1770
358	Colorado	Intimidation	1710
2286	Pennsylvania	Intimidation	1689
2227	Oregon	Intimidation	1619
428	Connecticut	Intimidation	1382
1021	Kentucky	Intimidation	1127
1950	North Carolina	Intimidation	1075
2503	Tennessee	Intimidation	1072
1547	Missouri	Intimidation	1052
816	Indiana	Intimidation	893
504	District of Columbia	Simple Assault	848
1134	Maine	Intimidation	633
2658	Utah	Destruction/Damage/Vandalism of Property	601
614	Georgia	Intimidation	598
939	Kansas	Intimidation	592
2167	Oklahoma	Intimidation	577
1685	Nevada	Destruction/Damage/Vandalism of Property	567

	state_name	offense_name	incident_id
2363	South Carolina	Destruction/Damage/Vandalism of Property	496
3054	Wisconsin	Destruction/Damage/Vandalism of Property	474
1627	Nebraska	Destruction/Damage/Vandalism of Property	424
470	Delaware	Destruction/Damage/Vandalism of Property	423
705	Idaho	Simple Assault	368
861	Iowa	Destruction/Damage/Vandalism of Property	343
527	Federal	Intimidation	329
2316	Rhode Island	Destruction/Damage/Vandalism of Property	328
1732	New Hampshire	Destruction/Damage/Vandalism of Property	296
2725	Vermont	Destruction/Damage/Vandalism of Property	287
3025	West Virginia	Simple Assault	252
170	Arkansas	Simple Assault	250
2439	South Dakota	Simple Assault	248
1817	New Mexico	Simple Assault	233
40	Alabama	Simple Assault	228
1107	Louisiana	Simple Assault	219
1587	Montana	Destruction/Damage/Vandalism of Property	200
2011	North Dakota	Simple Assault	147
656	Hawaii	Intimidation	128
3105	Wyoming	Simple Assault	79
48	Alaska	Aggravated Assault	75
1500	Mississippi	Simple Assault	69
641	Guam	Destruction/Damage/Vandalism of Property	7

In [45]:
```
df.columns
```

Out[45]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

Check pug_agency_name

In [46]:
```
df['pug_agency_name'].dtype
```

Out[46]:
```
dtype('O')
```

In [47]:
```
df['pug_agency_name'].unique()
```

Out[47]:
```
array(['Pine Bluff', 'North Little Rock', 'Sevier', ...,
       'Ohio Valley Drug and Violent Crime Task Force',
       'Berkeley Springs', 'Moorcroft'], shape=(7110,), dtype=object)
```

In [48]:
```
df['pug_agency_name'].isna().sum()
```

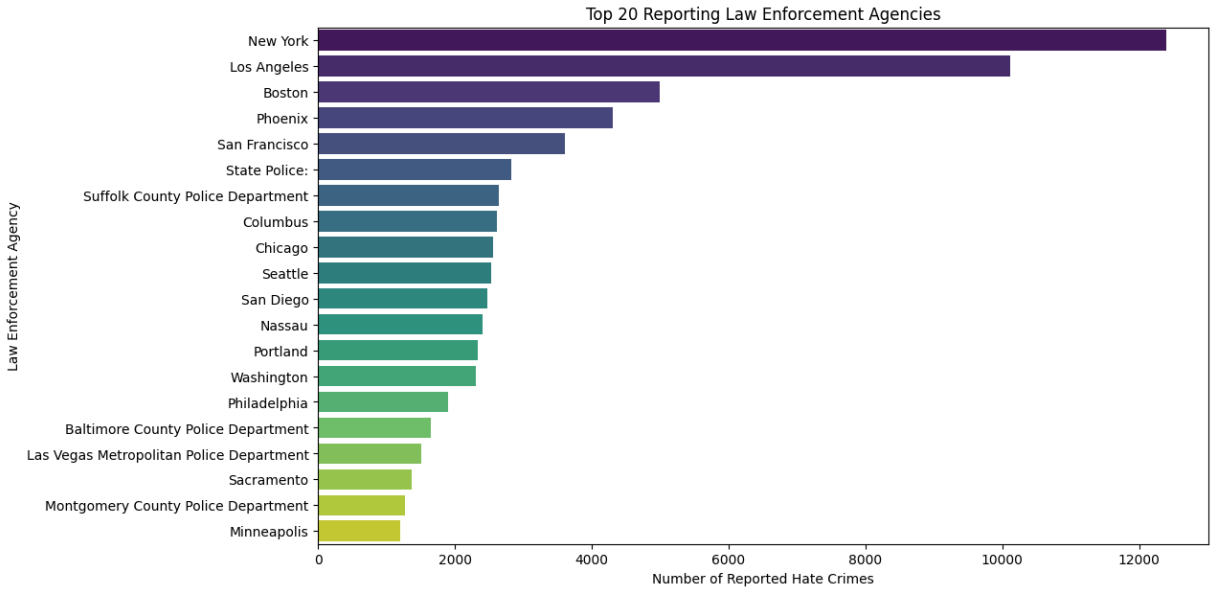
Out[48]:
```
np.int64(0)
```

In [49]:
```
df['pug_agency_name'].head()
```

Out[49]:
```
0           Pine Bluff
1           Pine Bluff
2    North Little Rock
3    North Little Rock
4               Sevier
Name: pug_agency_name, dtype: object
```

In [50]:
```
# Check distribution
# Check the distribution of 'pug_agency_name' (Law Enforcement Agency Names)

# Count occurrences of each agency
agency_counts = df["pug_agency_name"].value_counts().head(20)  # Top 20 most common

# Plot the distribution
plt.figure(figsize=(12, 7))
sns.barplot(x=agency_counts.values, y=agency_counts.index, palette="viridis")
plt.xlabel("Number of Reported Hate Crimes")
plt.ylabel("Law Enforcement Agency")
plt.title("Top 20 Reporting Law Enforcement Agencies")
plt.show()

print('New York has the top number of reporting hate crime via law enforement agenc
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\3350046672.py:9: FutureWarni
ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=agency_counts.values, y=agency_counts.index, palette="viridis")
```



New York has the top number of reporting hate crime via law enforement agencies

In [51]:
```
df.columns
```

Out[51]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

Check pub_agency_unit

In [52]:
```
df['pub_agency_unit'].dtype
```

Out[52]:
```
dtype('O')
```

In [53]:
```
df['pub_agency_unit'].unique()
```

Out[53]:
```
array([nan, 'Boulder', 'Urbana', 'Montgomery County', 'College Park',
       'Anne Arundel County', 'Carroll County', 'Cecil County',
       'Charles County', 'Frederick County', 'Harford County',
       "Queen Anne's County", 'Wicomico County', 'Worcester County',
       'Baltimore County', "Prince George's County", 'Twin Cities',
       'Albany', 'Binghamton', 'Cortland', 'Buffalo State College',
       'Morrisville', 'Old Westbury', 'Oswego', 'Potsdam', 'Stony Brook',
       'New Paltz', 'Purchase', 'Dutchess County', 'Orange County',
       'Oswego County', 'Sullivan County', 'Ulster County',
       'Wayne County', 'Delhi', 'Geneseo', 'Polytechnic Institute',
       'Columbus', 'Crook County', 'Curry County', 'Jackson County',
       'Lincoln County', 'Linn County', 'Marion County', 'Chester County',
       'Lancaster County', 'Monroe County', 'Washington County',
       'Westmoreland County', 'Blair County', 'Smyth County',
       'Wythe County', 'Milwaukee', 'East Bay', 'Fullerton',
       'Kent County', 'New Castle County', 'Sussex County', 'Tampa',
       'Tallahassee', 'Chicago', 'Calvert County', 'Caroline County',
       'Orono', 'Ann Arbor', 'Chapel Hill', 'Atlantic County',
       'Cape May County', 'Newark', 'Hunterdon County', 'Monmouth County',
       'Morris County', 'Salem County', 'Warren County', 'Camden County',
       'Cumberland County', 'Middlesex County', 'Alfred', 'Buffalo',
       'Oneonta', 'Farmingdale', 'Broome County', 'Columbia County (T)',
       'Niagara County', 'Oneida County', 'Oneida County (T)',
       'St. Lawrence County', 'Saratoga County', 'Westchester County',
       'Westchester County (T)', 'Fredonia', 'Brockport', 'Canton',
       'Norman', 'Lane County', 'Multnomah County', 'Benton County',
       'Skippack', 'Killeen', 'Downtown Campus', 'Klein', 'San Marcos',
       'Lubbock', 'Midland', 'Health and Sciences Center', 'Austin',
       'Amarillo', 'Pullman', 'Eau Claire', 'Fayetteville',
       'All Campuses', 'Zone 14A', 'District 3', 'District 4', 'Zone 4',
       'District 12', 'Carbondale', 'District 14', 'Edwardsville',
       'District 11', 'Indianapolis', 'Bloomington', 'Essex County',
       'Stony Creek Metropark', 'Burlington County', 'Mercer County',
       'Ocean County', 'Passaic County', 'Somerset County',
       'Gloucester County', 'Cobleskill', 'Chenango County',
       'Delaware County', 'Otsego County', 'Plattsburgh',
       'Klamath County', 'Tillamook County', 'Altoona', 'Butler County',
       'University Park', 'Elizabethville', 'Franklin County',
       'Indiana County', 'Lawrence County', 'Lehigh County',
       'Lycoming County', 'Pike County', 'Hope Valley', 'San Antonio',
       'Beaumont', 'Conroe', 'Commerce', 'Eastern', 'St. Albans', 'West',
       'Main Campus', 'Allegany County', 'Columbia', 'Reno',
       'Herkimer County', 'Onondaga County', 'Berks County',
       'Clearfield County', 'Crawford County', 'Fayette County',
       'Fulton County', 'Perry County', 'Knoxville',
       'Health Science Center', 'Spring Branch', 'Hanover County',
       'Salem', 'Rockbridge County', 'Powhatan County',
       'Spotsylvania County', 'St. Johnsbury', 'Rutland', 'Derby',
       'Shaftsbury', 'Brattleboro', 'Berlin', 'Alameda County',
       'Northridge', 'Los Angeles', 'Irvine', 'San Bernardino',
       'San Diego', 'San Luis Obispo', 'Oceano Dunes', 'San Jose',
       'San Francisco County', 'San Francisco', 'Pomona',
       'Contra Costa County', 'Colorado Springs', 'Health Center',
       'Southeast', 'Grant County', 'Letcher County', 'Mason County',
       'Union County', 'Amherst', 'Suffolk County', "St. Mary's County",
       'Farmington', 'Livingston County', 'Marquette County',
```

```
'Ogemaw County', 'Saginaw County', 'Van Buren County',
'Houghton County', 'Charlotte', 'Tompkins County',
'Deschutes County', 'Cambria County', 'Jefferson County', 'Judson',
'Spring', 'Tarrant County', 'Accomack County', 'Richmond County',
'Royalton', 'Platteville', 'Oshkosh', 'Berkeley',
'North Coast Redwoods', 'Dominguez Hills', 'Long Beach',
'Riverside', 'San Diego Coast', 'Davis', 'Northern Buttes',
'Fresno', 'Hancock County', 'Ohio County', 'Edmonson County',
'Floyd County', 'Rockcastle County', 'Scott County',
'Norfolk County', 'Medical Center, Worcester',
'Harbor Campus, Boston', 'Osceola County', 'Genesee County',
'Newaygo County', 'Harrisburg', 'East Central', 'College Station',
'Central Campus', 'Goochland County', 'Pittsylvania County',
'San Diego County', 'Sacramento', 'Santa Cruz', 'Fort Collins',
'Dartmouth', 'Talbot County', 'Flint', 'Greene County', 'Okmulgee',
'Tulsa', 'Chepachet', 'Martin', 'Corpus Christi', 'Arlington',
'Tazewell County', 'Fairfax County', 'New Haven', 'Parkside',
'Humboldt', 'Bakersfield', 'Medical Center, Sacramento',
'Bristol County', 'Baltimore City', 'Bay County',
'Chippewa County', 'Iosco County', 'Roscommon County',
'Washtenaw County', 'Clinton County', 'Ionia County',
'Oakland County', 'Adams County', 'Beaver County', 'El Paso',
'Pasadena', 'Logan', 'Arlington County', 'Santa Cruz ',
'Santa Barbara', 'Chico', 'Adair County', 'Hopkins County',
'Muhlenberg County', 'Plymouth County', 'Branch County',
'Cheboygan County', 'Gogebic County', 'Montcalm County', 'Duluth',
'Erie County', 'Albany County', 'Pittsburgh', 'Bucks County',
'Columbia County', 'Chattanooga', 'Waco', 'Pan American',
'Health Science Center, San Antonio', 'Clarke County',
'Rockingham', 'Huntington', 'Moorefield', 'Daviess County',
'McLean County', 'Madison County', 'Marshall County',
'Henderson County', 'Baton Rouge', 'Barry County', 'Lapeer County',
'Oxford', 'Cattaraugus County', 'Putnam County', 'Rockland County',
'Clatsop County', 'Armstrong County', 'Potter County',
'Bicentennial Capitol Mall', 'Clearlake', 'Denton',
'Southampton County', 'Bradford', 'Elizabeth', 'Marlinton',
'Berkeley County', 'Wyoming County', 'Health Sciences Center',
'Allen County', 'Wolfe County', 'Medford', 'Howard County',
'Grand Traverse County', 'Luce County', 'Eaton County',
'Gladwin County', 'Raleigh', 'Greensboro', 'Douglas County',
'Wasco County', '3rd Judicial District', 'Madison', 'Whitewater',
'Parsons', 'Moundsville', 'Upperglade', 'Carter County',
'Oldham County', 'Monroe', 'Shiawassee County', 'Dearborn',
'Clare County', 'Asheville', 'New York County', 'Schoharie County',
'Clackamas County', 'Josephine County', 'Superior', 'Rainelle',
'Orange Coast', 'Evanston', 'Lyon County', 'Kennebec County',
'Calhoun County', 'Kansas City', 'Maritime ', 'Juniata County',
'23rd Judicial District', 'Webster County', 'St. Petersburg',
'Crittenden County', 'Johnson County', 'Berkshire County',
'Hampden County', 'Muskegon County', 'Wexford County',
'St. Clair County', 'Wilmington', 'Ontario County', 'Berks',
'Centre County', 'Northampton County', 'Pickwick Landing',
'Dallas', 'Jonesboro', 'Monticello', 'Hastings College of Law',
'Monterey Bay', 'Troop B', 'Headquarters', 'Saratoga County (T)',
'Pymatuning', 'York County', 'Lexington County', 'Newberry County',
'Alvin', 'Tyler', 'Law Enforcement Division', 'Vancouver',
```

```
'La Crosse', 'Stanislaus', 'Aroostook County', 'Waldo County',
'St. Louis', 'Lincoln', 'Dillon County', 'Upstate', 'Green Bay',
'Gold Fields District', 'San Bernardino County', 'Auburn-Washburn',
'Isabella County', 'Kalamazoo County', 'Berrien County', 'Keyser',
'Romney', 'Medical Sciences', 'Medical Center',
'Kensington Metropark', 'Rensselaer County', 'Tioga County',
'Tahlequah', 'Schuylkill County', 'Dauphin County',
'San Luis Obispo ', 'Springfield', 'Maize', 'Goddard',
'Campbellsburg', 'Harlan', 'Madisonville', 'Pikeville', 'London',
'Wooster', 'Pine Bluff', 'Channel Islands', 'Pueblo', 'Mayfield',
'Bowling Green', 'Morehead', 'Dry Ridge', 'Androscoggin County',
'St. Joseph', 'Finger Lakes Region', 'Steuben County',
'Elk County', 'Permian Basin', 'Fauquier County', 'Morgantown',
'Frankfort', 'Orleans County', 'Anderson County', 'Little Rock',
'San Mateo County', 'Kewanee', 'Richmond', 'Ashland',
'Huron County', 'Institute of Technology', 'Plumas County',
'Tehachapi District', 'Henry County', 'Knox County', 'Lake County',
'Henderson', 'Cass County', 'Lower Huron Metropark', 'Morris',
'Long Island Region', 'Nassau County', 'Humble', 'Buchanan County',
'Rockingham County', 'Decatur County', 'Vanderburgh County',
'Hazard', 'Cannabis Suppression Section', 'Gratiot County',
'New York City Region', 'Huntingdon County', 'Greenwood County',
'Internal Affairs', 'Pflugerville', 'Halifax County', 'Stout',
'Miami County', 'Ripley County', 'Rush County', 'Jefferson City',
'Meramec', 'Pembroke', 'Johnstown', 'Dallas County', 'Houston',
'West Drug Enforcement Branch', 'Suffolk', 'Allegan County',
'Ingham County', 'Manistee County', 'Mecosta County',
'Oceana County', 'Downstate Medical ', 'Chemung County',
'Scituate', 'Sweetwater', 'Surry County', 'Chesapeake',
'Newport News', 'Enforcement Division', 'Marin County',
'La Porte County', 'Posey County', 'Troop E', 'Elizabethtown',
'Alpena County', 'St. Joseph County', 'Macomb County',
'Ottawa County', 'Grafton County', 'New Brunswick', 'Lewis County',
'Hamilton County', 'Brandywine', 'Rio Grande Valley',
'Amherst County', 'Winchester', 'Harrisonburg', 'Phoenix',
'Cincinnati', 'Albuquerque', 'Baltimore', 'Boston', 'Birmingham',
'Cleveland', 'Louisville', 'Memphis', 'Mobile', 'New Orleans',
'Omaha', 'Philadelphia', 'Portland', 'Seattle', 'Washington',
'Atlanta', 'Miami', 'Salt Lake City', 'Oklahoma City', 'Detroit',
'Office of Special Investigations', 'Spencer County', 'Troop A',
'Delta County', 'Schoolcraft County', 'Alger County',
'Hillsdale County', 'Arenac County', 'Central Region',
'Eastview Precinct', 'Cayuga County', 'Seneca County',
'Snyder County', 'Shenandoah County', 'Parkersburg', 'Anchorage',
'Denver', 'Jacksonville', 'Las Vegas', 'Minneapolis', 'New York',
'Norfolk', 'Elkhart County', 'Wabash County', 'Whitley County',
'Troop C', 'Ontonagon County', 'Mackinac County', 'Sanilac County',
'St. Paul', 'Camden', 'Schenectady County', 'Malheur County',
'Bradford County', 'Venango County', 'Hutto', 'Bay City',
'Brazosport', 'Prince William County', 'Dinwiddie County',
'Russell County', 'Staunton', 'Alleghany County',
'Division of Enforcement and Licensing', 'Princeton', 'Hamlin',
'Bridgeport', 'Wayne', 'Grantsville', 'Bay Area', 'Jackson',
'Honolulu', 'San Juan', 'South Bend', 'Baraga County',
'Midland County', 'Emmet County', 'Benzie County',
'Tuscola County', 'Hudson County', 'Southern Division',
```

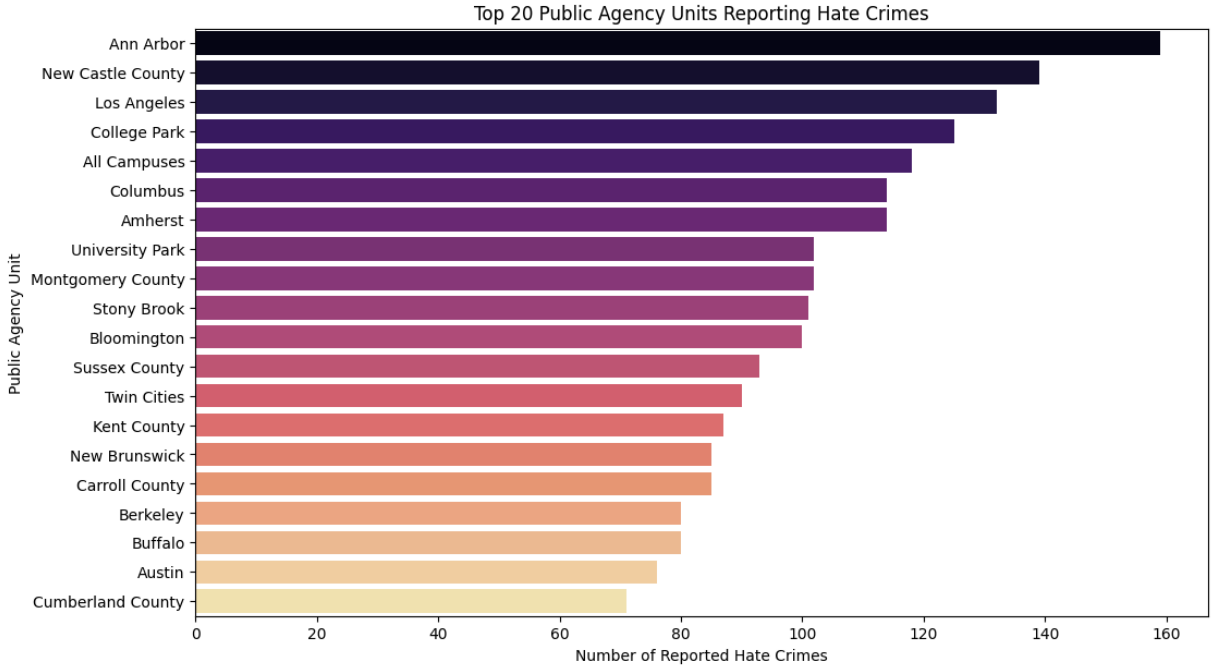
```
       'Chautauqua County', 'Chesterfield County', 'Colleton County',
       'Brunswick County', 'Roanoke', 'James City County',
       'Grayson County', 'Westminster', 'Williston', 'Beckley',
       'Berkeley Springs', 'Clay', 'Union', 'South Charleston',
       'Buckhannon', 'Elkins', 'Fire Investigation Division', 'Troop F',
       'Lowell', 'Environmental Police',
       'Internal Investigation Division', 'Prince Georges County',
       'Lenawee County', 'Cliffs of the Neuse', 'Northwestern Division',
       'Statewide', 'Genesee Region', 'Coos County', 'Allegheny County',
       'Tionesta', 'Bedford County', 'Philadelphia County',
       'Luzerne County', 'Northumberland County', 'York', 'Beaver',
       'Lackawanna County', 'Beaufort', 'Precinct 3', 'Anna',
       'Brownsville', 'Precinct 1', 'Burkburnett', 'Fort Bend',
       'Castleberry', 'Internet Crimes Against Children Unit',
       'Capitol Protection Section', 'Bishop Area Office', 'Troop G',
       'Health Sciences Center, Shreveport', 'Garrett County',
       "Queen Annes's County", 'Dorchester County', 'Leelanau County',
       'Kalkaska County', 'Hall County', 'Cheshire County',
       'Northeastern Division', 'Gilliam County', 'Clarion County',
       'Lebanon County', 'Montour County', 'Hazleton', 'Abington',
       'Susquehanna County', 'Round Rock', 'Mansfield', 'Katy', 'Hampton',
       'Culpeper County', 'Stevens Point', 'Martinsburg', 'Fairbanks',
       'Bakersfield ', 'Temecula Area Office', 'Marin Area Office',
       'Missaukee County', 'Kearney', 'Niagara Region', 'Allegany Region',
       'Umatilla County', 'Carbon County', 'Cameron County',
       'Kershaw County', 'Royal', 'Bastrop', 'Community',
       'Coldspring-Oakhurst', 'Eagle Mountain-Saginaw', 'Charlottesville',
       'Harrisville', 'Spencer', 'Grafton', 'Williamson', 'Fairmont'],
      dtype=object)
```

In [54]:
```
agency_unit_counts = df["pub_agency_unit"].value_counts().head(20)  # Top 20 most c
agency_unit_counts
```

Out[54]:
```
pub_agency_unit
Ann Arbor            159
New Castle County    139
Los Angeles          132
College Park         125
All Campuses         118
Columbus             114
Amherst              114
University Park      102
Montgomery County    102
Stony Brook          101
Bloomington          100
Sussex County         93
Twin Cities           90
Kent County           87
New Brunswick         85
Carroll County        85
Berkeley              80
Buffalo               80
Austin                76
Cumberland County     71
Name: count, dtype: int64
```

In [55]:
```
# Check distribution
plt.figure(figsize=(12, 7))
sns.barplot(x=agency_unit_counts.values, y=agency_unit_counts.index, palette="magma
plt.xlabel("Number of Reported Hate Crimes")
plt.ylabel("Public Agency Unit")
plt.title("Top 20 Public Agency Units Reporting Hate Crimes")
plt.show()

print('Top reporting public agencies include:\n1. Ann Arbor (highest reported hate
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\1034682908.py:3: FutureWarni
ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=agency_unit_counts.values, y=agency_unit_counts.index, palette="magm
a")
```




```
Top reporting public agencies include:
1. Ann Arbor (highest reported hate crimes!) → Diverse Student Population → Higher d
iversity sometimes leads to more reported bias-motivated incidents.  Strong Local Po
licies → Ann Arbor is known for progressive policies and a well-documented crime rep
orting system.
2. New Castle County & Los Angeles → Large urban areas with higher reported incident
s.
3. College Towns (e.g., College Park, University Park, Stony Brook, Bloomington) → M
any universities are in this list, meaning hate crimes in academic settings might be
a significant factor.
4. Counties & Urban Centers → Many counties like Montgomery, Carroll, Kent, and Suss
ex also appear, showing that hate crimes are not just in major cities.
```

Count the most common crime types reported by agencies unit

In [56]:
```
# Get top 20 public agency units
top_agency_units = df["pub_agency_unit"].value_counts().head(20).index
```

```
# Filter dataset to include only these top agencies
filtered_df = df[df["pub_agency_unit"].isin(top_agency_units)]

# Count the most common crime types reported by these agencies
crime_by_agency = filtered_df.groupby(["pub_agency_unit", "offense_name"])["inciden

# Get top crime types for each agency
top_crime_per_agency = crime_by_agency.sort_values(by="incident_id", ascending=Fals

# Display the result
top_crime_per_agency
```

Out[56]:

	pub_agency_unit	offense_name	incident_id
17	Ann Arbor	Destruction/Damage/Vandalism of Property	96
63	College Park	Destruction/Damage/Vandalism of Property	90
117	Montgomery County	Destruction/Damage/Vandalism of Property	90
11	Amherst	Destruction/Damage/Vandalism of Property	89
1	All Campuses	Destruction/Damage/Vandalism of Property	68
147	Stony Brook	Intimidation	65
48	Buffalo	Destruction/Damage/Vandalism of Property	62
53	Carroll County	Destruction/Damage/Vandalism of Property	62
159	Twin Cities	Destruction/Damage/Vandalism of Property	62
125	New Brunswick	Intimidation	53
133	New Castle County	Destruction/Damage/Vandalism of Property	49
110	Los Angeles	Intimidation	48
44	Bloomington	Intimidation	45
74	Columbus	Destruction/Damage/Vandalism of Property	44
32	Berkeley	Destruction/Damage/Vandalism of Property	43
25	Austin	Destruction/Damage/Vandalism of Property	38
96	Kent County	Destruction/Damage/Vandalism of Property	37
153	Sussex County	Destruction/Damage/Vandalism of Property	37
168	University Park	Intimidation	36
87	Cumberland County	Destruction/Damage/Vandalism of Property	35

Count the top bias moltivation reported by agencies unit

In [57]:

```
# Count bias motivations (e.g., race, religion, LGBTQ+) per agency
bias_by_agency = filtered_df.groupby(["pub_agency_unit", "bias_desc"])["incident_id
```

```
# Get top bias motivation for each agency
top_bias_per_agency = bias_by_agency.sort_values(by="incident_id", ascending=False)

# Display the result
print('Most of bias moltivations are racist like Anti-Black and Anti-Jewish')
top_bias_per_agency
```

```
Most of bias moltivations are racist like Anti-Black and Anti-Jewish
```

Out[57]:

	pub_agency_unit	bias_desc	incident_id
201	New Castle County	Anti-Black or African American	75
32	Ann Arbor	Anti-Black or African American	56
227	Sussex County	Anti-Black or African American	52
150	Kent County	Anti-Black or African American	51
178	Montgomery County	Anti-Black or African American	51
257	University Park	Anti-Black or African American	47
96	Carroll County	Anti-Black or African American	44
139	Cumberland County	Anti-Black or African American	41
216	Stony Brook	Anti-Black or African American	37
16	Amherst	Anti-Black or African American	36
2	All Campuses	Anti-Black or African American	36
46	Austin	Anti-Black or African American	35
120	Columbus	Anti-Black or African American	34
110	College Park	Anti-Black or African American	33
161	Los Angeles	Anti-Black or African American	31
76	Bloomington	Anti-Jewish	30
245	Twin Cities	Anti-Black or African American	28
194	New Brunswick	Anti-Jewish	26
88	Buffalo	Anti-Jewish	25
65	Berkeley	Anti-Jewish	21

In [58]:

```
df.columns
```

Out[58]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

Check agency_type_name

In [59]:
```
df['agency_type_name'].dtype
```

Out[59]:
```
dtype('O')
```

In [60]:
```
df['agency_type_name'].value_counts()
```

Out[60]:
```
agency_type_name
City                    202135
County                   36551
University or College     8456
State Police              3421
Other                     1759
Federal                    823
Other State Agency         504
Tribal                     127
Name: count, dtype: int64
```

In [61]:
```
df['agency_type_name'].unique()
```

Out[61]:
```
array(['City', 'County', 'Other State Agency', 'University or College',
       'State Police', 'Other', 'Tribal', 'Federal'], dtype=object)
```

In [62]:
```
# Count occurrences of each agency type
agency_type_counts = df["agency_type_name"].value_counts().head(10)  # Top 10 agenc

# Check distribution
plt.figure(figsize=(12, 7))

sns.barplot(x=agency_type_counts.values, y=agency_type_counts.index, palette="plasm
plt.xlabel("Number of Reported Hate Crimes")
plt.ylabel("Agency Type")
plt.title("Top 10 Agency Types Reporting Hate Crimes")

plt.show()
print('City Police Departments report the most hate crimes → Likely because cities
```

```
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ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=agency_type_counts.values, y=agency_type_counts.index, palette="plas
ma")
```

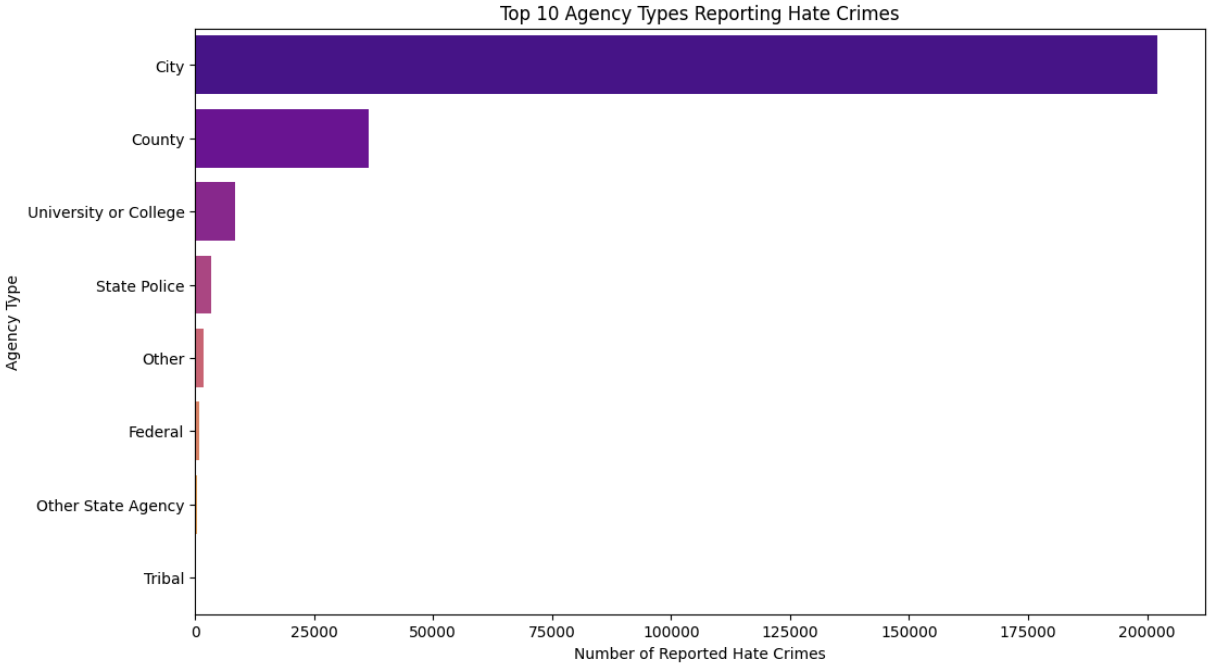

City Police Departments report the most hate crimes → Likely because cities have higher population density & more incidents.

In [63]:
```
# Compare Hate Crime Types Across Different Agency Types

# Count most common crime types for each agency type
crime_by_agency_type = df.groupby(["agency_type_name", "offense_name"])["incident_i

# Get top crime type per agency type
top_crime_per_agency_type = crime_by_agency_type.sort_values(by="incident_id", asce

# Display the result
top_crime_per_agency_type
```

Out[63]:

	agency_type_name	offense_name	incident_id
277	City	Intimidation	61115
464	County	Destruction/Damage/Vandalism of Property	12539
795	University or College	Destruction/Damage/Vandalism of Property	4289
709	State Police	Destruction/Damage/Vandalism of Property	966
611	Other	Destruction/Damage/Vandalism of Property	659
585	Federal	Intimidation	330
651	Other State Agency	Destruction/Damage/Vandalism of Property	230
765	Tribal	Intimidation	33

In [64]:
```
# Most Common Bias Motivations (Race, Religion, LGBTQ) per Agency Type

# Count bias motivations for each agency type
bias_by_agency_type = df.groupby(["agency_type_name", "bias_desc"])["incident_id"].

# Get top bias motivation per agency type
top_bias_per_agency_type = bias_by_agency_type.sort_values(by="incident_id", ascend

# Display the result
top_bias_per_agency_type
```

Out[64]:

	agency_type_name	bias_desc	incident_id
94	City	Anti-Black or African American	66193
391	County	Anti-Black or African American	13245
721	University or College	Anti-Black or African American	2734
639	State Police	Anti-Black or African American	1375
551	Other	Anti-Black or African American	527
497	Federal	Anti-Black or African American	266
597	Other State Agency	Anti-Black or African American	171
688	Tribal	Anti-American Indian or Alaska Native	34

In [65]:
```
# Check if Certain Agencies Report Disproportionately High or Low Crimes

# Count total hate crimes per agency type
agency_type_totals = df.groupby("agency_type_name")["incident_id"].count().reset_in

# Rename the column 'incident_id' to 'incident_id_count'
agency_type_totals = agency_type_totals.rename(columns={"incident_id": "incident_id

# Normalize by percentage to see distribution
agency_type_totals["percentage"] = (agency_type_totals["incident_id_count"] / agenc
```

```
# Display the result
agency_type_totals
```

Out[65]:

	agency_type_name	incident_id_count	percentage
0	City	202135	79.650952
1	County	36551	14.402859
2	Federal	823	0.324302
3	Other	1759	0.693131
4	Other State Agency	504	0.198600
5	State Police	3421	1.348039
6	Tribal	127	0.050044
7	University or College	8456	3.332072

In [66]:
```
df.columns
```

Out[66]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

Check state abbr

In [67]:
```
df['state_abbr'].dtype
```

Out[67]:
```
dtype('O')
```

In [68]:
```
df['state_abbr'].unique()
```

Out[68]:
```
array(['AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'GA', 'IA', 'ID', 'IL',
       'KS', 'MA', 'MD', 'MN', 'MO', 'MS', 'NJ', 'NV', 'NY', 'OH', 'OK',
       'OR', 'PA', 'TN', 'TX', 'VA', 'WA', 'WI', 'AL', 'FL', 'IN', 'KY',
       'LA', 'ME', 'MI', 'NC', 'ND', 'RI', 'SC', 'UT', 'WY', 'AK', 'MT',
       'NM', 'SD', 'VT', 'NH', 'NB', 'WV', 'GM', 'FS', 'HI'], dtype=object)
```

In [69]:
```
df['state_abbr'].isna().sum()
```

Out[69]:
```
np.int64(0)
```

In [70]:
```
# Check distribution
# Count occurrences of each state abbreviation
state_abbr_counts = df["state_abbr"].value_counts()  # Top 20 states by reported ha
```

```
# Plot the distribution of state abbreviations reporting hate crimes
plt.figure(figsize=(16, 9))

sns.barplot(x=state_abbr_counts.index, y=state_abbr_counts.values, palette="coolwar
plt.xlabel("State Abbreviation")
plt.ylabel("Number of Reported Hate Crimes")
plt.title("Top 20 States Reporting Hate Crimes (State Abbreviations)")
plt.xticks(rotation=45)

plt.show()
print('This is the same result as total reported hate crime per state that we plott
```

```
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ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=state_abbr_counts.index, y=state_abbr_counts.values, palette="coolwa
rm")
```
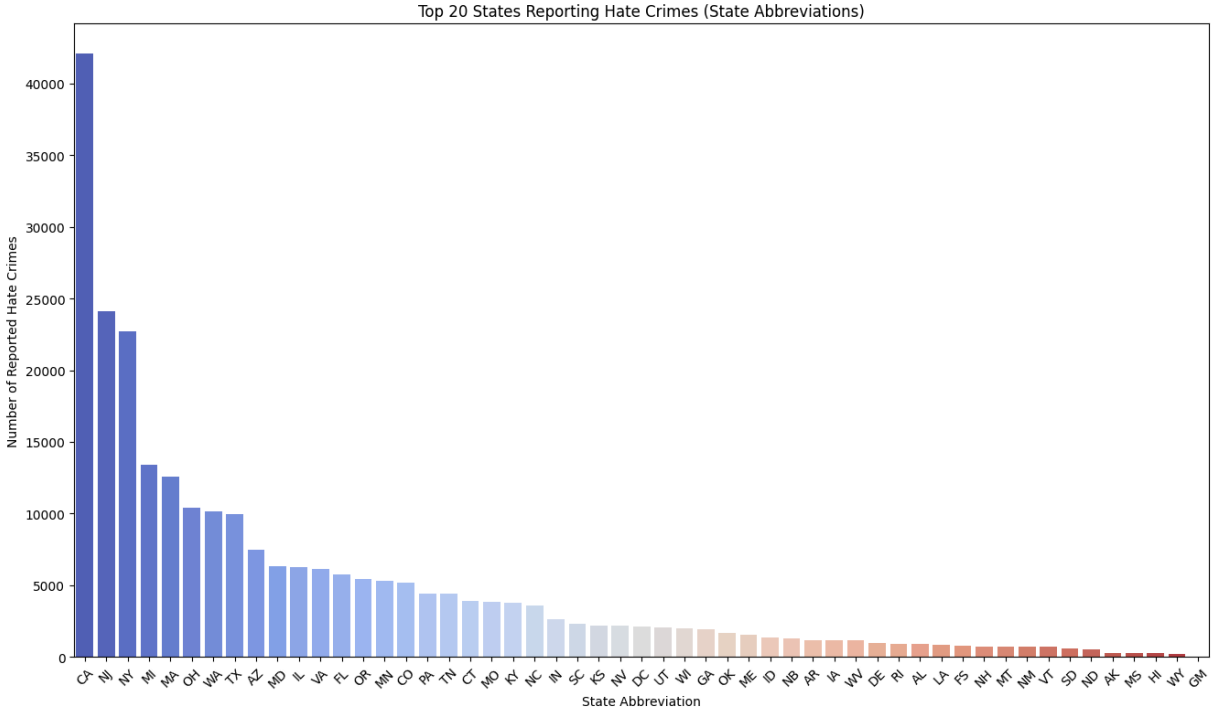



This is the same result as total reported hate crime per state that we plotted befor
e due to being abbreviation word from the actual state

In [71]:
```
df.columns
```

Out[71]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

Check division_name

In [72]:
```
df['division_name'].dtype
```

Out[72]:
```
dtype('O')
```

In [73]:
```
df['division_name'].value_counts()
```

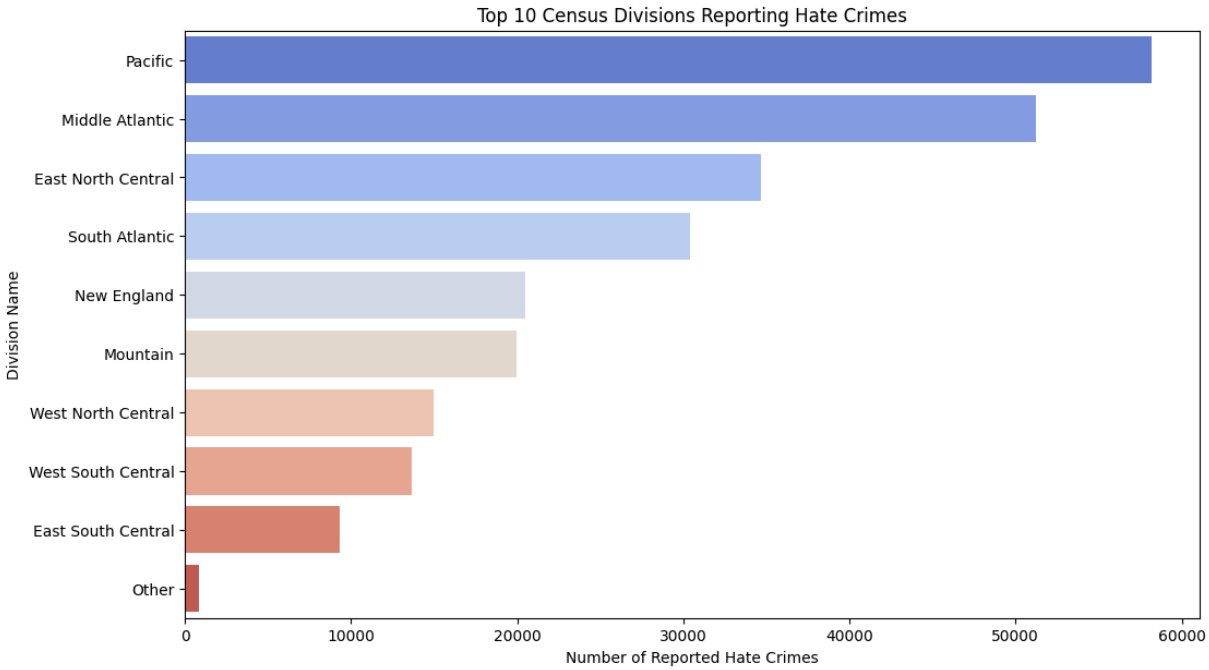
Out[73]:
```
division_name
Pacific                58182
Middle Atlantic        51258
East North Central     34687
South Atlantic         30389
New England            20460
Mountain               19985
West North Central     14959
West South Central     13682
East South Central      9329
Other                    820
U.S. Territories          25
Name: count, dtype: int64
```

In [74]:
```
df['division_name'].isna().sum()
```

Out[74]:
```
np.int64(0)
```

In [75]:
```
# Check distribution
# Count occurrences of each division name
division_counts = df["division_name"].value_counts().head(10)  # Top 10 divisions b

# Plot the distribution of hate crimes per division
plt.figure(figsize=(12, 7))

sns.barplot(x=division_counts.values, y=division_counts.index, palette="coolwarm")
plt.xlabel("Number of Reported Hate Crimes")
plt.ylabel("Division Name")
plt.title("Top 10 Census Divisions Reporting Hate Crimes")

plt.show()
print('Pacific Division reports the most hate crimes → Likely due to California, wh
print('Note: California is in the Pacific census division, the geographical regions
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\3886282386.py:8: FutureWarni
ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=division_counts.values, y=division_counts.index, palette="coolwarm")
```



Pacific Division reports the most hate crimes → Likely due to California, which had the highest state-level reports.
Note: California is in the Pacific census division, the geographical regions defined by the U.S. just like Central Region and Northeastern Region in Thailand

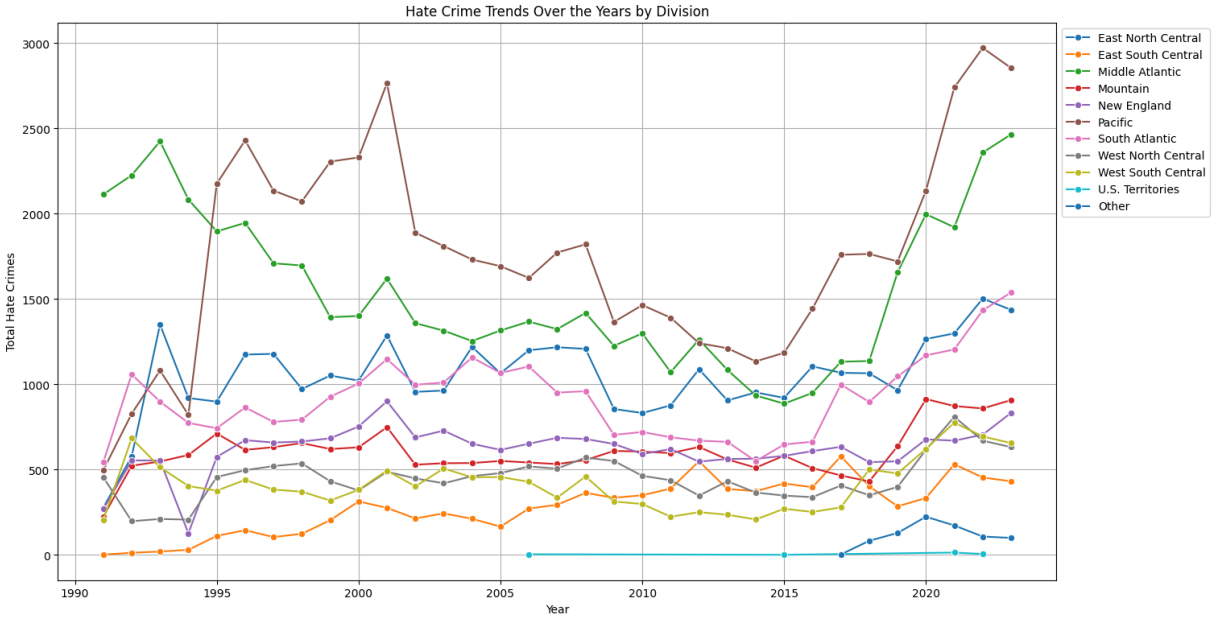
In [76]:
```
# Compare Most Common Hate Crime Types in Each Division

# Count most common crime types for each division
crime_by_division = df.groupby(["division_name", "offense_name"])["incident_id"].co

# Get top crime type per division
top_crime_per_division = crime_by_division.sort_values(by="incident_id", ascending=

# Display the result
top_crime_per_division
```

Out[76]:

	division_name	offense_name	incident_id
391	Middle Atlantic	Intimidation	20143
845	Pacific	Destruction/Damage/Vandalism of Property	16561
1023	South Atlantic	Destruction/Damage/Vandalism of Property	10691
127	East North Central	Intimidation	10531
680	New England	Intimidation	6793
539	Mountain	Intimidation	5112
1209	West North Central	Intimidation	4091
1305	West South Central	Destruction/Damage/Vandalism of Property	3230
285	East South Central	Intimidation	2423
745	Other	Intimidation	329
1112	U.S. Territories	Destruction/Damage/Vandalism of Property	7

In [77]:

```
# Trends Over Time: Hate Crime Changes in Each Division

# Aggregate crime trends per division over years
crime_trend_by_division = df.groupby(["data_year", "division_name"])["incident_id"]

# Plot trends over time
plt.figure(figsize=(16, 9))

sns.lineplot(data=crime_trend_by_division, x="data_year", y="incident_id", hue="div
plt.xlabel("Year")
plt.ylabel("Total Hate Crimes")
plt.title("Hate Crime Trends Over the Years by Division")
plt.legend(loc="upper left", bbox_to_anchor=(1, 1))
plt.grid(True)

plt.show()

print('Pacific & Middle Atlantic divisions show consistently higher hate crime repo
print('Sharp increases post-2015, suggesting changes in social dynamics or improved
```



Pacific & Middle Atlantic divisions show consistently higher hate crime reports. Sharp increases post-2015, suggesting changes in social dynamics or improved reporting.

In [78]:
```
df.columns
```

Out[78]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

Check region_name

In [79]:
```
df['region_name'].dtype
```

Out[79]:
```
dtype('O')
```

In [80]:
```
df['region_name'].value_counts()
```

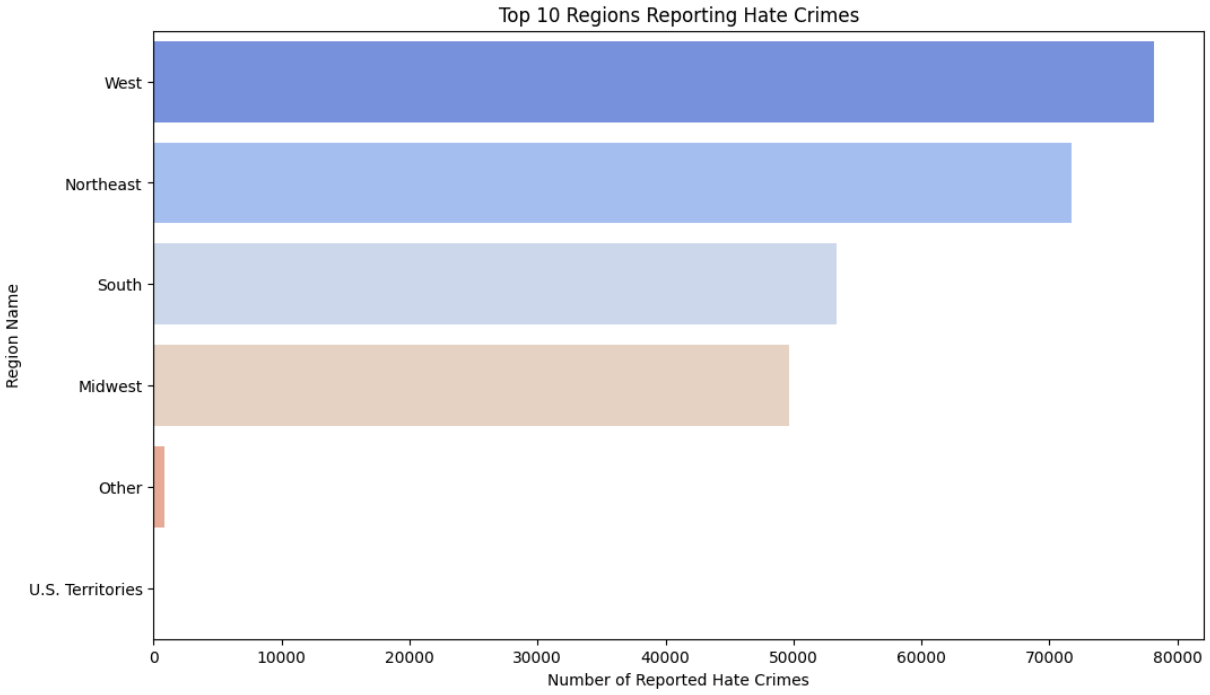
Out[80]:
```
region_name
West                78167
Northeast           71718
South               53400
Midwest             49646
Other                 820
U.S. Territories       25
Name: count, dtype: int64
```

In [81]:
```
df['region_name'].isna().sum()
```

Out[81]: np.int64(0)

In [82]:
```
# Check distribution
# Count occurrences of each region name
region_counts = df["region_name"].value_counts().head(10)  # Top 10 regions by repo

# Plot the distribution of hate crimes per region
plt.figure(figsize=(12, 7))

sns.barplot(x=region_counts.values, y=region_counts.index, palette="coolwarm")
plt.xlabel("Number of Reported Hate Crimes")
plt.ylabel("Region Name")
plt.title("Top 10 Regions Reporting Hate Crimes")

plt.show()
print('The West reports the most hate crimes → Likely driven by California's high r
print('The Northeast follows closely → Includes states like New York and New Jersey
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\966949114.py:8: FutureWarnin
g:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x=region_counts.values, y=region_counts.index, palette="coolwarm")
```




```
The West reports the most hate crimes → Likely driven by California's high reporting
numbers.
The Northeast follows closely → Includes states like New York and New Jersey, which
have strict reporting requirements.
```

In [83]:
```
# Most Common Bias Motivations (Race, Religion, LGBTQ) in Each Region

# Count bias motivations per region
bias_by_region = df.groupby(["region_name", "bias_desc"])["incident_id"].count().re
```

```
# Get top bias motivation per region
top_bias_per_region = bias_by_region.sort_values(by="incident_id", ascending=False)

# Display the result
top_bias_per_region
```

Out[83]:

	region_name	bias_desc	incident_id
663	West	Anti-Black or African American	23727
183	Northeast	Anti-Black or African American	22418
497	South	Anti-Black or African American	19471
21	Midwest	Anti-Black or African American	18648
419	Other	Anti-Black or African American	266
617	U.S. Territories	Anti-White	8

In [84]:
```
df.columns
```

Out[84]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

Check population_group_code and population_group_description

In [85]:
```
df['population_group_code'].dtype
```

Out[85]:
```
dtype('O')
```

In [86]:
```
df['population_group_code'].unique()
```

Out[86]:
```
array(['3', '8D', '5', '6', '2', '1B', '1C', '9B', '4', '9A', '7', '8C',
       '1A', '9D', '9C', '8B', '8A', '8E', '9E', '0', nan], dtype=object)
```

In [87]:
```
df['population_group_code'].isna().sum()
```

Out[87]:
```
np.int64(667)
```

In [88]:
```
df['population_group_description'].dtype
```

Out[88]:
```
dtype('O')
```

In [89]:
```
df['population_group_description'].unique()
```

Out[89]:
```
array(['Cities from 50,000 thru 99,999', 'Non-MSA counties under 10,000',
       'Cities from 10,000 thru 24,999', 'Cities from 2,500 thru 9,999',
       'Cities from 100,000 thru 249,999',
       'Cities from 500,000 thru 999,999',
       'Cities from 250,000 thru 499,999',
       'MSA counties from 25,000 thru 99,999',
       'Cities from 25,000 thru 49,999', 'MSA counties 100,000 or over',
       'Cities under 2,500', 'Non-MSA counties from 10,000 thru 24,999',
       'Cities 1,000,000 or over', 'MSA counties under 10,000',
       'MSA counties from 10,000 thru 24,999',
       'Non-MSA counties from 25,000 thru 99,999',
       'Non-MSA counties 100,000 or over', 'Non-MSA State Police',
       'MSA State Police',
       'Possessions (Puerto Rico, Guam, Virgin Islands, and American Samoa)',
       nan], dtype=object)
```

In [90]:
```
df['population_group_description'].isna().sum()
```

Out[90]:
```
np.int64(667)
```

In [91]:
```
# Count occurrences of each population group (Code + Description)

# Count hate crimes per population group
population_group_counts = df.groupby(["population_group_code", "population_group_de

# Sort by highest reported hate crimes
population_group_counts = population_group_counts.sort_values(by="incident_id", asc

# Display the result
print('Biggest cities (1,000,000+ population) report the most hate crimes (36,210 c
population_group_counts
```

```
Biggest cities (1,000,000+ population) report the most hate crimes (36,210 cases).
  - Large urban centers like New York, Los Angeles, and Chicago drive these numbers.
  - More people = more reported incidents & better reporting infrastructure.
```

Out[91]:

	population_group_code	population_group_description	incident_id
1	1A	Cities 1,000,000 or over	36210
5	3	Cities from 50,000 thru 99,999	28356
6	4	Cities from 25,000 thru 49,999	28156
2	1B	Cities from 500,000 thru 999,999	24915
7	5	Cities from 10,000 thru 24,999	24756
4	2	Cities from 100,000 thru 249,999	24338
15	9A	MSA counties 100,000 or over	23190
3	1C	Cities from 250,000 thru 499,999	17275
8	6	Cities from 2,500 thru 9,999	15245
9	7	Cities under 2,500	13438
16	9B	MSA counties from 25,000 thru 99,999	6761
11	8B	Non-MSA counties from 25,000 thru 99,999	2441
12	8C	Non-MSA counties from 10,000 thru 24,999	2321
18	9D	MSA counties under 10,000	2005
13	8D	Non-MSA counties under 10,000	1968
17	9C	MSA counties from 10,000 thru 24,999	1154
10	8A	Non-MSA counties 100,000 or over	270
14	8E	Non-MSA State Police	238
19	9E	MSA State Police	47
0	0	Possessions (Puerto Rico, Guam, Virgin Islands...	25

In [92]:

```
# Compare Most Common Hate Crime Types in Different Population Groups

# Count most common crime types for each population group
crime_by_population_group = df.groupby(["population_group_description", "offense_na

# Get top crime type per population group
top_crime_per_population_group = crime_by_population_group.sort_values(by="incident

# Display the result
print('Vandalism (Destruction/Damage of Property) is the most common hate crime in
top_crime_per_population_group
```

```
Vandalism (Destruction/Damage of Property) is the most common hate crime in large ci
ties (1M+ people).
  - Biggest cities (New York, LA, Chicago) see more property-related hate crimes tha
n violent offenses.
  - Higher population density + diverse communities might lead to more bias-related
vandalism (graffiti, destruction, etc.).
```

Out[92]:

	population_group_description	offense_name	incident_id
44	Cities 1,000,000 or over	Destruction/Damage/Vandalism of Property	11245
1287	MSA counties 100,000 or over	Destruction/Damage/Vandalism of Property	9597
654	Cities from 25,000 thru 49,999	Intimidation	9458
935	Cities from 50,000 thru 99,999	Intimidation	9003
200	Cities from 10,000 thru 24,999	Intimidation	8552
1078	Cities from 500,000 thru 999,999	Intimidation	8087
359	Cities from 100,000 thru 249,999	Intimidation	6774
1166	Cities under 2,500	Destruction/Damage/Vandalism of Property	5755
780	Cities from 250,000 thru 499,999	Intimidation	4913
505	Cities from 2,500 thru 9,999	Intimidation	4706
1491	MSA counties from 25,000 thru 99,999	Intimidation	1762
1792	Non-MSA counties from 25,000 thru 99,999	Intimidation	566
1559	MSA counties under 10,000	Destruction/Damage/Vandalism of Property	516
1728	Non-MSA counties from 10,000 thru 24,999	Simple Assault	508
1879	Non-MSA counties under 10,000	Simple Assault	419
1371	MSA counties from 10,000 thru 24,999	Destruction/Damage/Vandalism of Property	303
1646	Non-MSA counties 100,000 or over	Intimidation	99
1616	Non-MSA State Police	Intimidation	64
1230	MSA State Police	Simple Assault	12
1896	Possessions (Puerto Rico, Guam, Virgin Islands...	Simple Assault	7

In [93]:
```
df.columns
```

Out[93]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias'],
      dtype='object')
```

In [94]:
```
# Categorize Hate Crimes into Violent vs. Non-Violent Categories

# Define violent and non-violent crime categories
violent_crimes = ["Aggravated Assault", "Simple Assault", "Murder", "Rape", "Robber
non_violent_crimes = ["Destruction/Damage/Vandalism of Property", "Intimidation", "

# Create a new column classifying each offense as violent or non-violent
df["crime_type"] = df["offense_name"].apply(lambda x: "Violent" if x in violent_cri

# Count violent vs. non-violent hate crimes by population group
crime_type_by_population = df.groupby(["population_group_description", "crime_type"

# Pivot for visualization
crime_type_pivot = crime_type_by_population.pivot(index="population_group_descripti

# Display the result
print('Non-Violent Crimes (Vandalism, Intimidation) are the most common across all
crime_type_pivot
```

```
Non-Violent Crimes (Vandalism, Intimidation) are the most common across all city siz
es.
```

Out[94]:

crime_type	Non-Violent	Other	Violent
population_group_description			
Cities 1,000,000 or over	20066	1547	14597
Cities from 10,000 thru 24,999	16074	2732	5950
Cities from 100,000 thru 249,999	13408	2468	8462
Cities from 2,500 thru 9,999	8957	2219	4069
Cities from 25,000 thru 49,999	18234	2653	7269
Cities from 250,000 thru 499,999	8882	1484	6909
Cities from 50,000 thru 99,999	17468	2645	8243
Cities from 500,000 thru 999,999	12967	1744	10204
Cities under 2,500	9564	1274	2600
MSA State Police	18	8	21
MSA counties 100,000 or over	15275	1796	6119
MSA counties from 10,000 thru 24,999	537	255	362
MSA counties from 25,000 thru 99,999	3503	1222	2036
MSA counties under 10,000	916	414	675
Non-MSA State Police	106	93	39
Non-MSA counties 100,000 or over	167	48	55
Non-MSA counties from 10,000 thru 24,999	917	630	774
Non-MSA counties from 25,000 thru 99,999	1065	588	788
Non-MSA counties under 10,000	756	548	664
Possessions (Puerto Rico, Guam, Virgin Islands, and American Samoa)	11	5	9

In [95]:
```
# Break Down Specific Violent Crime Types by Population Group

# Filter only violent crimes
violent_crime_types = df[df["crime_type"] == "Violent"]

# Count occurrences of each violent crime type per population group
violent_crime_by_population = violent_crime_types.groupby(["population_group_descri

# Get top violent crime per population group
top_violent_crime_per_population = violent_crime_by_population.sort_values(by="inci

# Display the result
print('"Simple Assault" is the most common violent hate crime across all city sizes
```

```
print('  - Largest cities (1M+ people) report the most Simple Assault cases (8,443)
print('Violent hate crimes occur in all city sizes, not just big cities.')
print('  - Cities from 25K-49K still report 4,716 incidents of Simple Assault.')
top_violent_crime_per_population
```

```
"Simple Assault" is the most common violent hate crime across all city sizes.
  - Largest cities (1M+ people) report the most Simple Assault cases (8,443).
Violent hate crimes occur in all city sizes, not just big cities.
  - Cities from 25K-49K still report 4,716 incidents of Simple Assault.
```

Out[95]:

	population_group_description	offense_name	incident_id
3	Cities 1,000,000 or over	Simple Assault	8443
31	Cities from 500,000 thru 999,999	Simple Assault	5931
27	Cities from 50,000 thru 99,999	Simple Assault	5118
11	Cities from 100,000 thru 249,999	Simple Assault	4902
19	Cities from 25,000 thru 49,999	Simple Assault	4716
7	Cities from 10,000 thru 24,999	Simple Assault	3917
23	Cities from 250,000 thru 499,999	Simple Assault	3863
41	MSA counties 100,000 or over	Simple Assault	3851
15	Cities from 2,500 thru 9,999	Simple Assault	2749
35	Cities under 2,500	Simple Assault	1886
49	MSA counties from 25,000 thru 99,999	Simple Assault	1377
63	Non-MSA counties from 10,000 thru 24,999	Simple Assault	508
67	Non-MSA counties from 25,000 thru 99,999	Simple Assault	505
53	MSA counties under 10,000	Simple Assault	461
71	Non-MSA counties under 10,000	Simple Assault	419
45	MSA counties from 10,000 thru 24,999	Simple Assault	245
59	Non-MSA counties 100,000 or over	Simple Assault	43
56	Non-MSA State Police	Simple Assault	25
37	MSA State Police	Simple Assault	12
73	Possessions (Puerto Rico, Guam, Virgin Islands...	Simple Assault	7

In [96]:

```
df.columns
```

Out[96]:
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type'],
      dtype='object')
```

Check incident_date

In [97]:
```
df['incident_date'].dtype
```

Out[97]:
```
dtype('O')
```

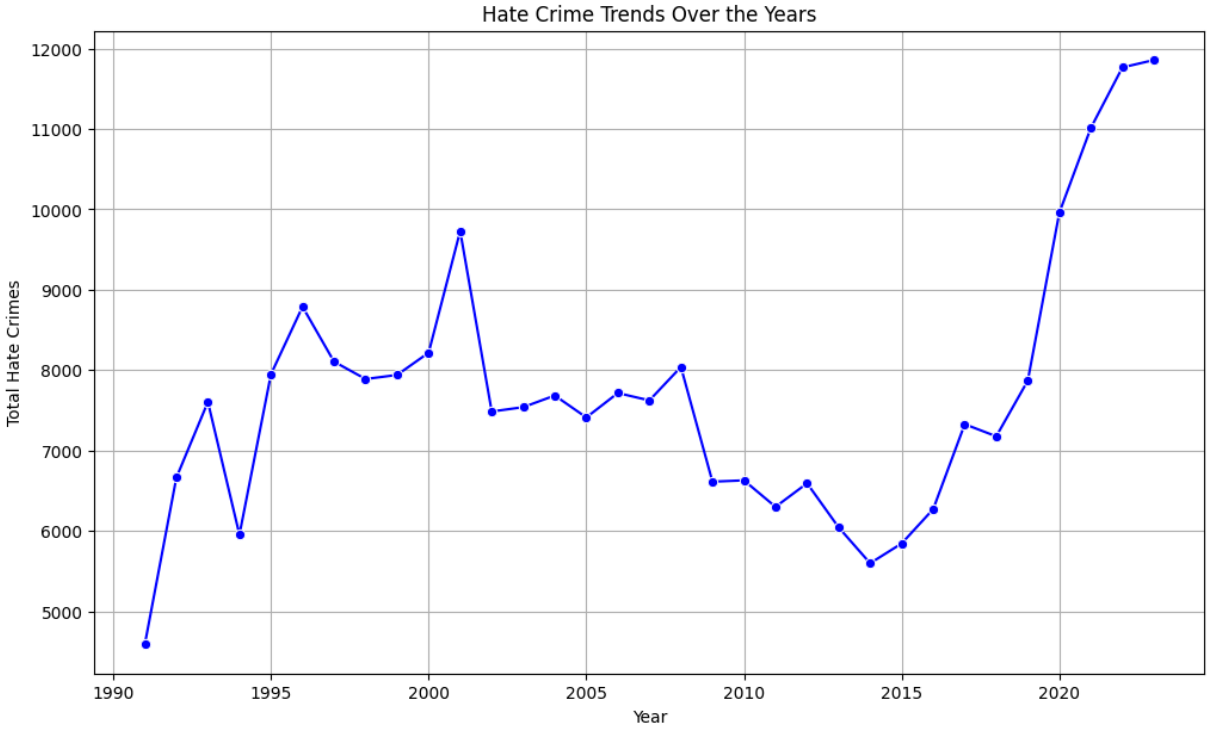
In [98]:
```
df['incident_date'].unique()
```

Out[98]:
```
array(['1991-07-04', '1991-12-24', '1991-07-10', ..., '2023-06-30',
       '2023-04-09', '2023-04-17'], shape=(12053,), dtype=object)
```

In [99]:
```
df['incident_date'].isna().sum()
```

Out[99]:
```
np.int64(0)
```

In [100…
```
# Check distribution
# Convert 'incident_date' to datetime format before extracting year
df["incident_date"] = pd.to_datetime(df["incident_date"])

# Extract year from the incident_date column
df["year"] = df["incident_date"].dt.year

# Count total hate crimes per year
yearly_trends = df.groupby("year")["incident_id"].count().reset_index()

# Plot trends over years
plt.figure(figsize=(12, 7))

sns.lineplot(data=yearly_trends, x="year", y="incident_id", marker="o", color="blue
plt.xlabel("Year")
plt.ylabel("Total Hate Crimes")
plt.title("Hate Crime Trends Over the Years")
plt.grid(True)

plt.show()
print('Sharp rise in the early 1990s')
print('  - Hate crime reports spiked quickly between 1991-1993.\n')
print('Post-2015 resurgence of hate crimes')
print('  - A sharp increase from 2016-2020, reaching new highs.')
print('  - This could be influenced by political climate, social unrest, or more ac
```




```
Sharp rise in the early 1990s
  - Hate crime reports spiked quickly between 1991-1993.

Post-2015 resurgence of hate crimes
  - A sharp increase from 2016-2020, reaching new highs.
  - This could be influenced by political climate, social unrest, or more active rep
orting.
```

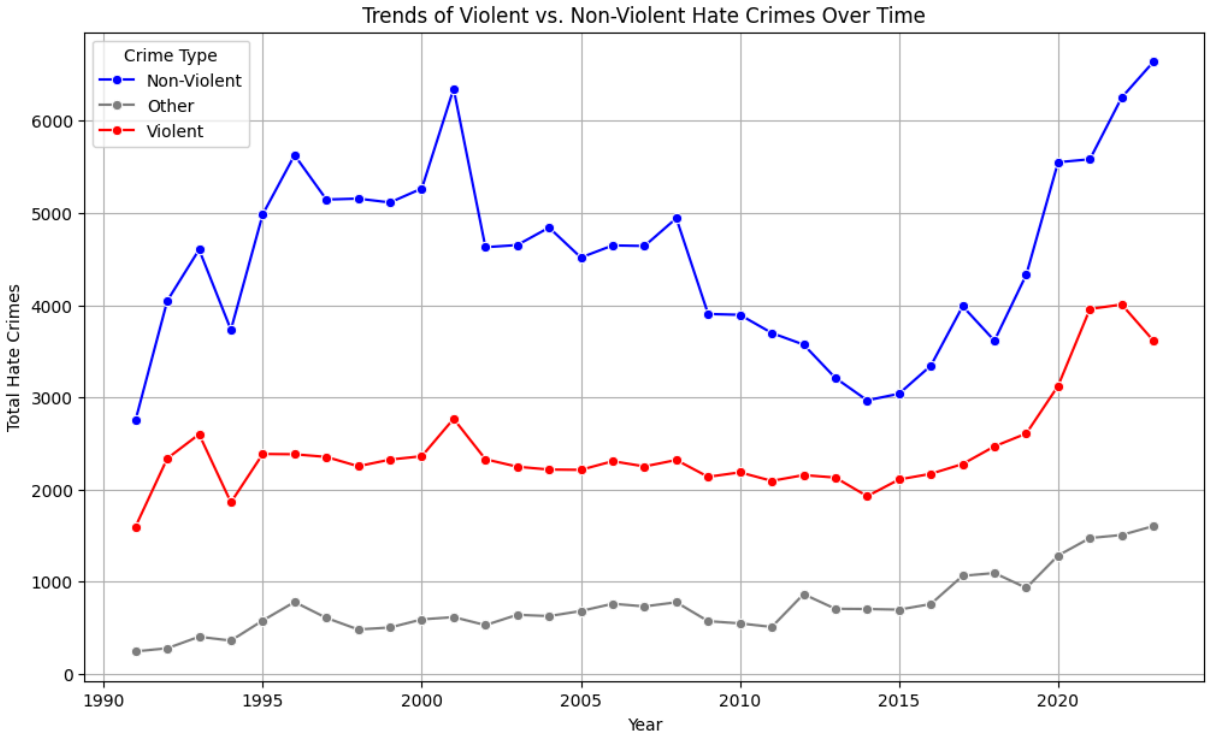
Concern

- ถ้าเอา year มาอาจจะเป็น time-series มาเอี่ยวด้วย
- มันจะดูเหมาะกว่ารึไหมว่า predict feature นี้ว่าปีนี้ crime ประเภทไร

In [101…

```python
# Compare Trends of Violent vs. Non-Violent Hate Crimes Over Time

# Aggregate crime type counts per year
crime_type_trends = df.groupby(["year", "crime_type"])["incident_id"].count().reset

# Plot trends over years
plt.figure(figsize=(12, 7))

sns.lineplot(data=crime_type_trends, x="year", y="incident_id", hue="crime_type", m
plt.xlabel("Year")
plt.ylabel("Total Hate Crimes")
plt.title("Trends of Violent vs. Non-Violent Hate Crimes Over Time")
plt.legend(title="Crime Type")
plt.grid(True)

plt.show()
print('Non-Violent Hate Crimes (Blue Line) have always been more frequent than Viol
print('Violent Hate Crimes (Red Line) remained steady but increased post-2015.')
print('  - Violent offenses (e.g., assaults, murder, robbery) stayed stable from th
```

```
print('  - Post-2015, violent crimes started rising again.\n')
print('Recent years (2020+) show a sharp increase in both categories.')
print('  - Potential reasons include social movements, political events, law enforc
print('The "Other" category (Gray Line) remains consistently low.')
print('  - Other category includes Burglary/ Breaking & Entering and Shoplifting')
print('  - These are crimes that do not fall under the standard "Violent" or "Non-V
```

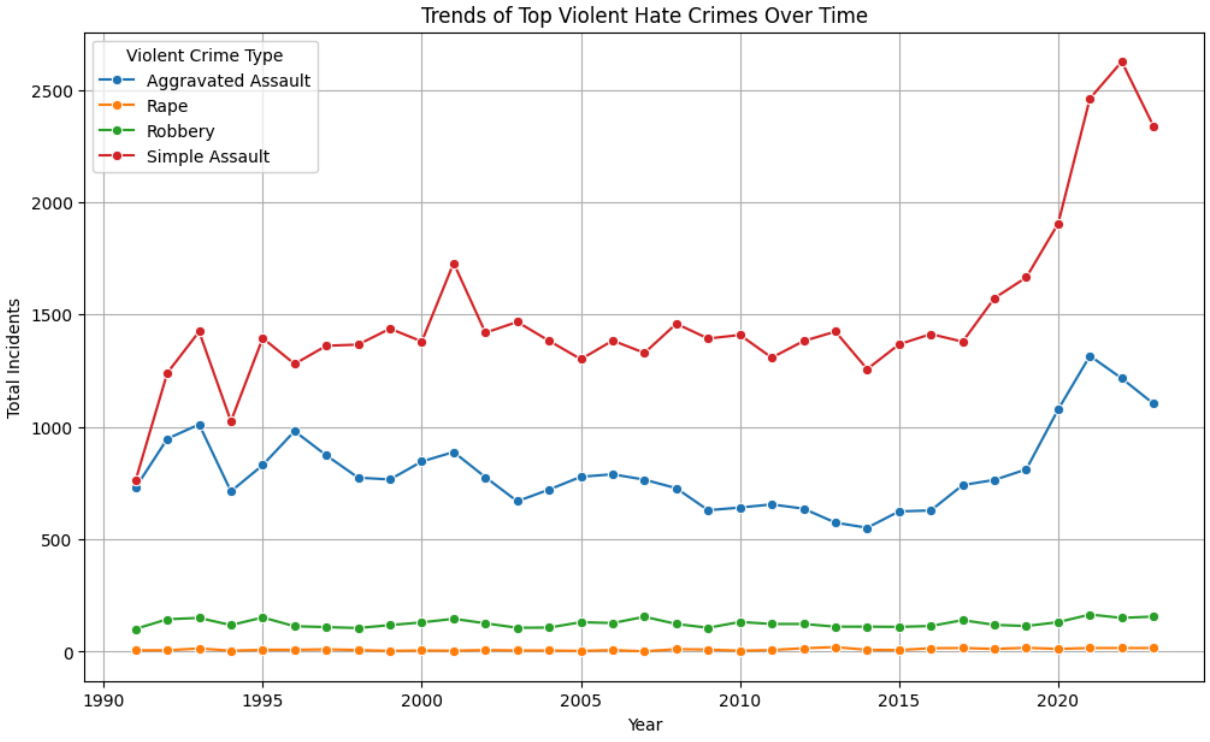



```
Non-Violent Hate Crimes (Blue Line) have always been more frequent than Violent one
s.

Violent Hate Crimes (Red Line) remained steady but increased post-2015.
  - Violent offenses (e.g., assaults, murder, robbery) stayed stable from the mid-19
90s to mid-2010s.
  - Post-2015, violent crimes started rising again.

Recent years (2020+) show a sharp increase in both categories.
  - Potential reasons include social movements, political events, law enforcement ch
anges, or better reporting mechanisms.

The "Other" category (Gray Line) remains consistently low.
  - Other category includes Burglary/ Breaking & Entering and Shoplifting
  - These are crimes that do not fall under the standard "Violent" or "Non-Violent"
categories but are still recorded as hate crimes.
```

In [102…

```
# Breakdown of Violent Crime Types Over Time

# Filter only violent crimes
violent_crimes_over_time = df[df["crime_type"] == "Violent"]

# Count occurrences of each violent crime type per year
violent_crime_trends = violent_crimes_over_time.groupby(["year", "offense_name"])["

# Get the top 5 most common violent crime types
top_violent_crimes = violent_crime_trends.groupby("offense_name")["incident_id"].su
```

```
# Filter data to only include the top 5 violent crime types
violent_crime_trends_filtered = violent_crime_trends[violent_crime_trends["offense_

# Plot trends over years
plt.figure(figsize=(12, 7))

sns.lineplot(data=violent_crime_trends_filtered, x="year", y="incident_id", hue="of
plt.xlabel("Year")
plt.ylabel("Total Incidents")
plt.title("Trends of Top Violent Hate Crimes Over Time")
plt.legend(title="Violent Crime Type")
plt.grid(True)

plt.show()
print('Simple Assault (Pink Line) is the most common violent hate crime.')
print('  - Increased significantly after 2015.')
print('  - Massive spike in 2020+, reaching over 2,500 cases per year.\n')
print('Aggravated Assault (Orange Line) is the second most common.')
print('  - Generally steady from 1990s-2015 but saw a major rise post-2018.')
print('  - Highest recorded increase in 2020-2022.\n')
print('Robbery (Red Line) has remained low but steady.')
print('  - It fluctuates around the 100-200 cases per year range.\n')
print('Rape (Light Orange Line) is the least reported violent hate crime.')
print('  - Consistently low throughout all years, with very slight fluctuations.')
```



Simple Assault (Pink Line) is the most common violent hate crime.
- Increased significantly after 2015.
- Massive spike in 2020+, reaching over 2,500 cases per year.

Aggravated Assault (Orange Line) is the second most common.
- Generally steady from 1990s-2015 but saw a major rise post-2018.
- Highest recorded increase in 2020-2022.

Robbery (Red Line) has remained low but steady.
- It fluctuates around the 100-200 cases per year range.

Rape (Light Orange Line) is the least reported violent hate crime.
- Consistently low throughout all years, with very slight fluctuations.

In [103…
```
df.columns
```

Out[103…
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year'],
      dtype='object')
```

Check adult_victim_count

In [104…
```
df['adult_victim_count'].dtype
```

Out[104…
```
dtype('float64')
```

In [105…
```
df['adult_victim_count'].unique()
```

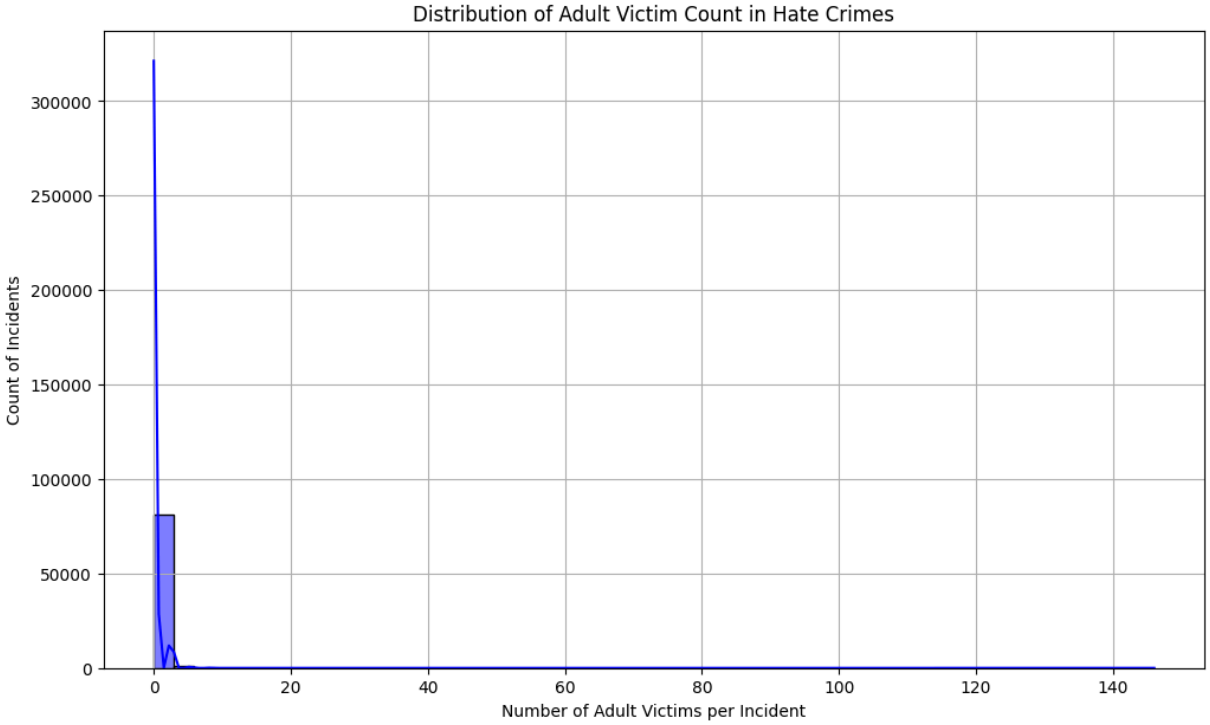
Out[105…
```
array([ nan,   1.,   0.,   3.,   2.,   4.,   7.,   6.,   5.,   9.,  12.,
        13.,  10.,  75.,  14.,   8.,  26.,  27.,  50.,  17.,  80.,  43.,
        15., 146.,  20.,  60.,  40.,  21.])
```

In [106…
```
df['adult_victim_count'].isna().sum()
```

Out[106…
```
np.int64(171076)
```

In [107…
```
# Check distribution

# Plot the distribution of adult victim counts
plt.figure(figsize=(12, 7))

sns.histplot(df["adult_victim_count"], bins=50, kde=True, color="blue")
plt.xlabel("Number of Adult Victims per Incident")
plt.ylabel("Count of Incidents")
plt.title("Distribution of Adult Victim Count in Hate Crimes")
plt.grid(True)

plt.show()
```

```
print('Most incidents involve 0-2 adult victims.')
print('  - The distribution is heavily skewed toward 0 or 1 adult victim per case.'
print('  - The mean (average) is ~0.75 victims per incident.\n')
print('A few extreme cases have 10+ adult victims.')
print('  - Some incidents involved dozens of victims (outliers beyond 100+).')
print('  - These might be mass hate crimes, large group attacks, or systemic discri
```




```
Most incidents involve 0-2 adult victims.
  - The distribution is heavily skewed toward 0 or 1 adult victim per case.
  - The mean (average) is ~0.75 victims per incident.

A few extreme cases have 10+ adult victims.
  - Some incidents involved dozens of victims (outliers beyond 100+).
  - These might be mass hate crimes, large group attacks, or systemic discrimination
cases.
```

Check juvenile_victim_count

In [108…
```
df['juvenile_victim_count'].dtype
```

Out[108…
```
dtype('float64')
```

In [109…
```
df['juvenile_victim_count'].unique()
```

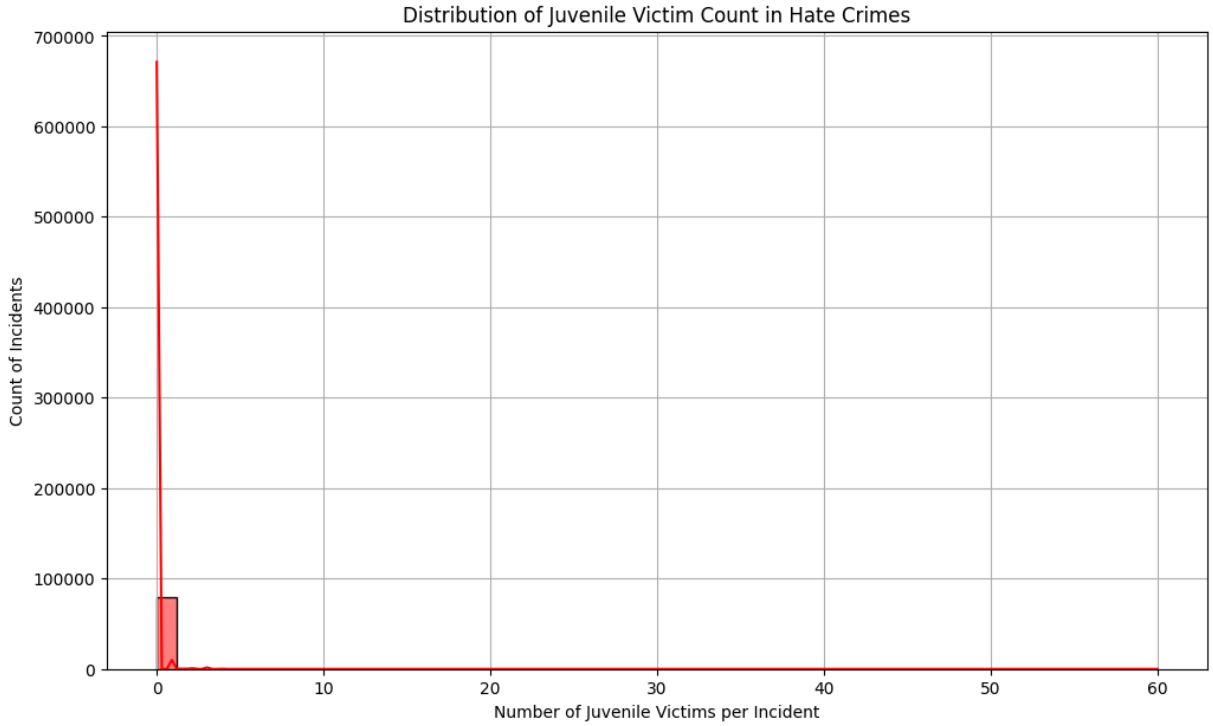
Out[109…
```
array([nan,  0.,  4.,  1.,  2.,  3.,  5., 40.,  9.,  6., 10.,  7., 20.,
       8., 29., 60., 12., 18.])
```

In [110…
```
df['juvenile_victim_count'].isna().sum()
```

Out[110…
```
np.int64(173713)
```

In [111…
```
# Check distribution
```

```
# Plot the distribution of juvenile victim counts
plt.figure(figsize=(12, 7))

sns.histplot(df["juvenile_victim_count"], bins=50, kde=True, color="red")
plt.xlabel("Number of Juvenile Victims per Incident")
plt.ylabel("Count of Incidents")
plt.title("Distribution of Juvenile Victim Count in Hate Crimes")
plt.grid(True)

plt.show()
```



In [112…

```
# Compare Victim Counts Across Different Crime Types

# Aggregate average number of victims per crime type
victim_by_crime_type = df.groupby("offense_name")[["adult_victim_count", "juvenile_

# Display the result
print('Hate crimes overwhelmingly target adults.')
print('  - Most crimes involve 0-2 adult victims, with very few cases affecting lar
print('Juvenile victim counts are extremely low.')
print('  - Most hate crimes do not involve juvenile victims at all.\n')
print('Certain violent crimes (Aggravated Assault) involve more adult victims.')
print('  - Aggravated Assault = ~0.92 adult victims per case.\n')
victim_by_crime_type
```

```
Hate crimes overwhelmingly target adults.
  - Most crimes involve 0-2 adult victims, with very few cases affecting large group
s.

Juvenile victim counts are extremely low.
  - Most hate crimes do not involve juvenile victims at all.

Certain violent crimes (Aggravated Assault) involve more adult victims.
  - Aggravated Assault = ~0.92 adult victims per case.
```

Out[112…

	offense_name	adult_victim_count	juvenile_victim_count
0	Aggravated Assault	0.923640	0.108435
1	Aggravated Assault;All Other Larceny	0.923077	0.000000
2	Aggravated Assault;All Other Larceny;Burglary/...	0.000000	0.000000
3	Aggravated Assault;All Other Larceny;Destructi...	1.000000	0.000000
4	Aggravated Assault;All Other Larceny;Extortion...	4.000000	0.000000
...	...	...	...
418	Theft of Motor Vehicle Parts or Accessories	0.705357	0.008929
419	Treason	0.000000	0.000000
420	Weapon Law Violations	0.000000	0.000000
421	Welfare Fraud	1.000000	0.000000
422	Wire Fraud	0.833333	0.055556

423 rows × 3 columns

In [113…

```
df.columns
```

Out[113…

```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year'],
      dtype='object')
```

Check total_offender_count

In [114…

```
df['total_offender_count'].dtype
```

Out[114…
```
dtype('int64')
```

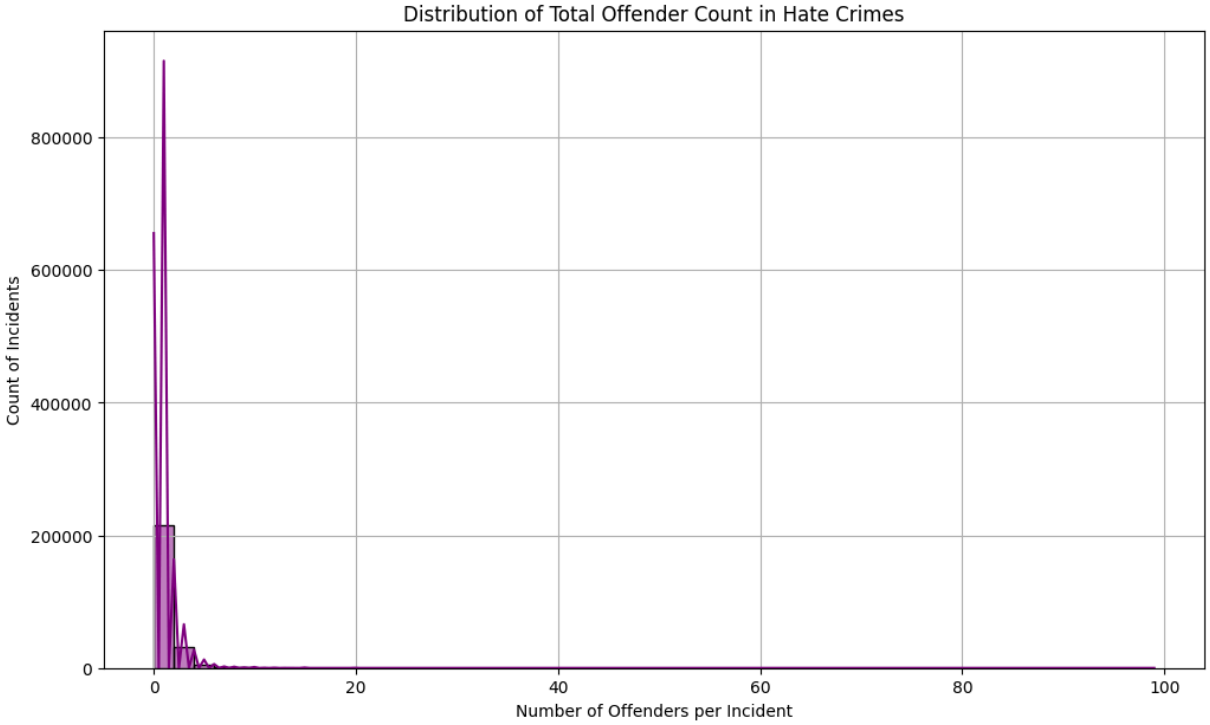
In [115…
```
df['total_offender_count'].unique()
```

Out[115…
```
array([ 1,  2, 10,  0,  5,  4,  6,  3, 11, 12, 26, 25,  8,  9, 40,  7, 35,
       17, 16, 20, 13, 30, 15, 14, 50, 29, 22, 99, 75, 18, 21, 23, 60, 36])
```

In [116…
```
df['total_offender_count'].isna().sum()
```

Out[116…
```
np.int64(0)
```

In [121…
```
# Check distribution

# Plot the distribution of total offender counts
plt.figure(figsize=(12, 7))

sns.histplot(df["total_offender_count"], bins=50, kde=True, color="purple")
plt.xlabel("Number of Offenders per Incident")
plt.ylabel("Count of Incidents")
plt.title("Distribution of Total Offender Count in Hate Crimes")
plt.grid(True)

plt.show()

# Summary statistics
print(f"Summary statistic of total_offender_count:\n\n{df['total_offender_count'].d
print('Most incidents involve only 1 offender.')
print('  - The mean (average) is ~0.95 offenders per incident, which means most cas
print('  - A huge spike at 0 and 1 offenders, suggesting some cases lack a known of
print('Some incidents involve multiple offenders.')
print('  - A small number of cases involve more than 5-10 offenders.')
print('  - This could indicate group-based hate crimes, extremist activities, or ga
print('Outliers exist (cases with 20+ offenders).')
print('  - Some hate crimes involve organized attacks or large groups acting togeth
print('  - These cases could be riots, mob violence, or targeted mass hate crimes.'
```




```
Summary statistic of total_offender_count:

count    253776.000000
mean          0.949542
std           1.298449
min           0.000000
25%           0.000000
50%           1.000000
75%           1.000000
max          99.000000
Name: total_offender_count, dtype: float64


Most incidents involve only 1 offender.
  - The mean (average) is ~0.95 offenders per incident, which means most cases invol
ve a single perpetrator.
  - A huge spike at 0 and 1 offenders, suggesting some cases lack a known offender
(reported but unsolved).

Some incidents involve multiple offenders.
  - A small number of cases involve more than 5-10 offenders.
  - This could indicate group-based hate crimes, extremist activities, or gang-relat
ed incidents.

Outliers exist (cases with 20+ offenders).
  - Some hate crimes involve organized attacks or large groups acting together.
  - These cases could be riots, mob violence, or targeted mass hate crimes.
```

In [122…

```
df.columns
```

Out[122…
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year'],
      dtype='object')
```

Check adult_offender_count

In [123…
```
df['adult_offender_count'].dtype
```

Out[123…
```
dtype('float64')
```

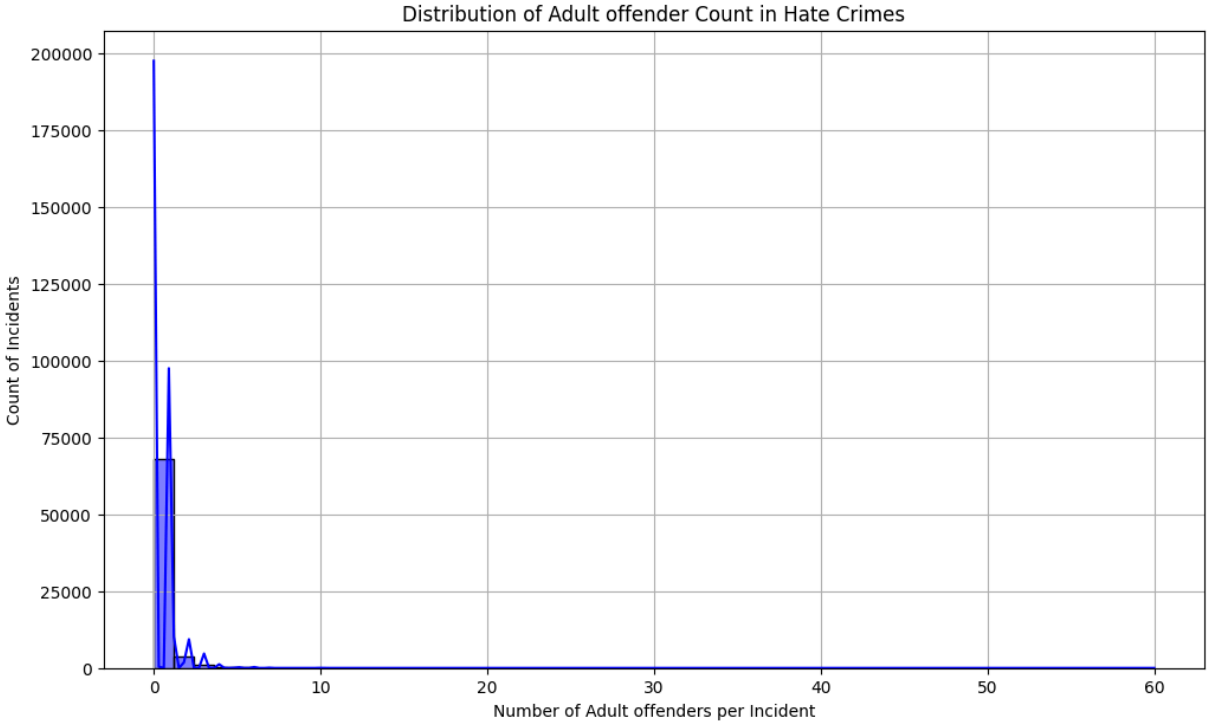
In [124…
```
df['adult_offender_count'].unique()
```

Out[124…
```
array([nan,  1.,  0.,  4.,  2.,  3.,  5.,  9.,  6.,  7.,  8., 20., 13.,
       19., 10., 30., 60., 15.])
```

In [125…
```
df['adult_offender_count'].isna().sum()
```

Out[125…
```
np.int64(180557)
```

In [126…
```
# Check distribution
# Plot the distribution of adult offender counts
plt.figure(figsize=(12, 7))

sns.histplot(df["adult_offender_count"], bins=50, kde=True, color="blue")
plt.xlabel("Number of Adult offenders per Incident")
plt.ylabel("Count of Incidents")
plt.title("Distribution of Adult offender Count in Hate Crimes")
plt.grid(True)

plt.show()
```



Check juvenile_offender_count

In [127…
```
df['juvenile_offender_count'].dtype
```

Out[127…
```
dtype('float64')
```

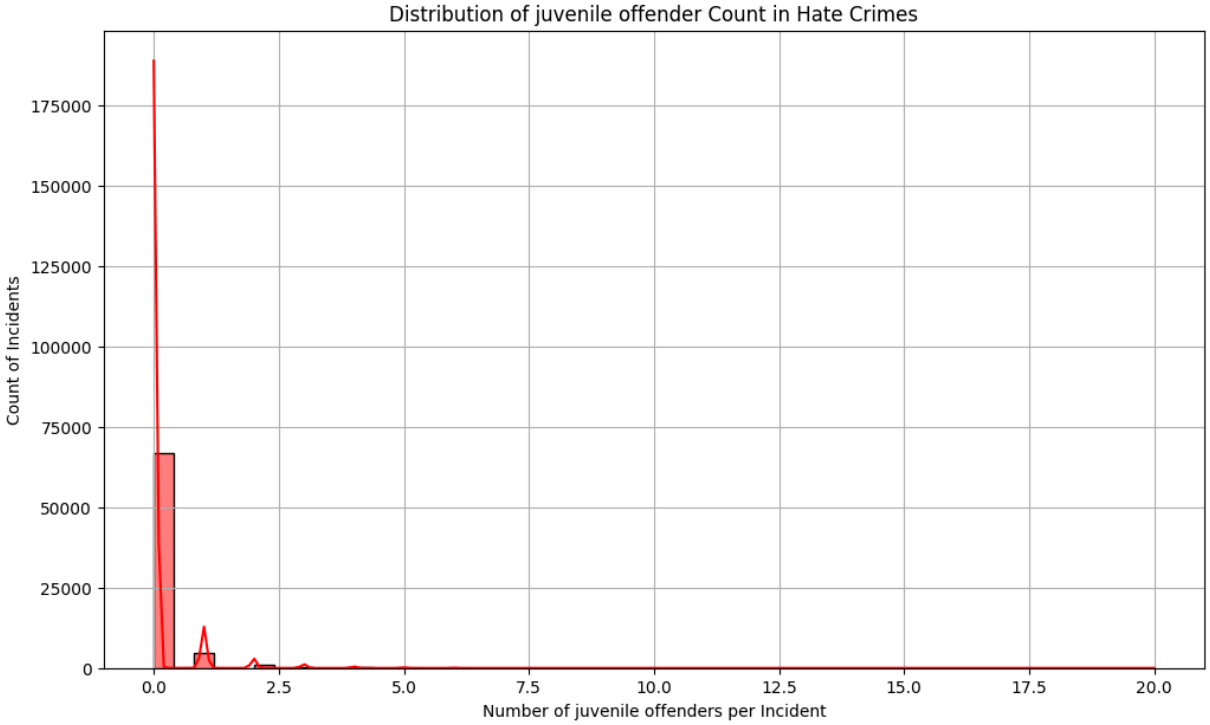
In [128…
```
df['juvenile_offender_count'].unique()
```

Out[128…
```
array([nan,  0.,  1.,  3.,  2.,  5.,  6.,  4., 13.,  7., 12., 10.,  9.,
       15., 11., 20.,  8.])
```

In [129…
```
df['juvenile_offender_count'].isna().sum()
```

Out[129…
```
np.int64(180564)
```

In [130…
```
# Check distribution
# Plot the distribution of juvenile offender counts
plt.figure(figsize=(12, 7))

sns.histplot(df["juvenile_offender_count"], bins=50, kde=True, color="red")
plt.xlabel("Number of juvenile offenders per Incident")
plt.ylabel("Count of Incidents")
plt.title("Distribution of juvenile offender Count in Hate Crimes")
plt.grid(True)

plt.show()
```



In [131…

```
# Compare Adult vs. Juvenile Offender Counts

# Summary statistics for juvenile offender count
juvenile_offender_summary = df["juvenile_offender_count"].describe()

# Display comparison summary for both adult and juvenile offender counts
offender_summary = pd.DataFrame({
    "Total Offender Count": df["total_offender_count"].describe(),
    "Adult Offender Count": df["adult_offender_count"].describe(),
    "Juvenile Offender Count": df["juvenile_offender_count"].describe()
})

# Display the result
print('Hate crimes are overwhelmingly committed by adult offenders.')
print('  - The mean adult offender count is ~0.89 per incident, while juvenile offe
print('  - Most hate crimes involve only one adult offender.')
offender_summary
```

```
Hate crimes are overwhelmingly committed by adult offenders.
  - The mean adult offender count is ~0.89 per incident, while juvenile offenders ar
e much lower (~0.09 per incident).
  - Most hate crimes involve only one adult offender.
```

Out[131…

	Total Offender Count	Adult Offender Count	Juvenile Offender Count
count	253776.000000	73219.000000	73212.000000
mean	0.949542	0.623090	0.128804
std	1.298449	0.808085	0.531138
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	1.000000	1.000000	0.000000
75%	1.000000	1.000000	0.000000
max	99.000000	60.000000	20.000000

In [132…

```
# Compare Offender Counts Across Different Crime Types

# Aggregate average number of offenders per crime type
offender_by_crime_type = df.groupby("offense_name")[["total_offender_count", "adult

# Display the result
print('Aggravated Assault involves the most offenders (~1.64 per case).')
print('  - Hate-motivated physical violence is more likely to involve multiple atta
print('Combination Crimes (multiple offenses at once) tend to have the highest offe
print('  - Cases where multiple crimes occur at once (e.g., assault + robbery + van
print('Some crimes involve mostly juvenile offenders.')
print('  - A few rare cases had juvenile-only offender groups.')
print('  - These could be related to gang-related activity or school-based hate cri
offender_by_crime_type
```

```
Aggravated Assault involves the most offenders (~1.64 per case).
  - Hate-motivated physical violence is more likely to involve multiple attackers.

Combination Crimes (multiple offenses at once) tend to have the highest offender cou
nts.
  - Cases where multiple crimes occur at once (e.g., assault + robbery + vandalism)
often involve more than one offender.

Some crimes involve mostly juvenile offenders.
  - A few rare cases had juvenile-only offender groups.
  - These could be related to gang-related activity or school-based hate crimes.
```

Out[132...

	offense_name	total_offender_count	adult_offender_count	juvenile_offender_count
0	Aggravated Assault	1.637726	0.892724	0.094683
1	Aggravated Assault;All Other Larceny	1.478261	0.600000	0.500000
2	Aggravated Assault;All Other Larceny;Burglary/...	2.000000	0.000000	0.000000
3	Aggravated Assault;All Other Larceny;Destructi...	1.500000	2.000000	0.000000
4	Aggravated Assault;All Other Larceny;Extortion...	4.000000	0.000000	4.000000
...	...	...	...	...
418	Theft of Motor Vehicle Parts or Accessories	0.354701	0.333333	0.060606
419	Treason	1.000000	1.000000	0.000000
420	Weapon Law Violations	1.182013	0.946360	0.114943
421	Welfare Fraud	0.200000	1.000000	0.000000
422	Wire Fraud	0.615385	0.250000	0.000000

423 rows × 4 columns

In [133...

```
df.columns
```

Out[133...

```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year'],
      dtype='object')
```

Check offender_race

In [134...

```
df['offender_race'].dtype
```

Out[134… dtype('O')

In [135…
```
df['offender_race'].value_counts()
```

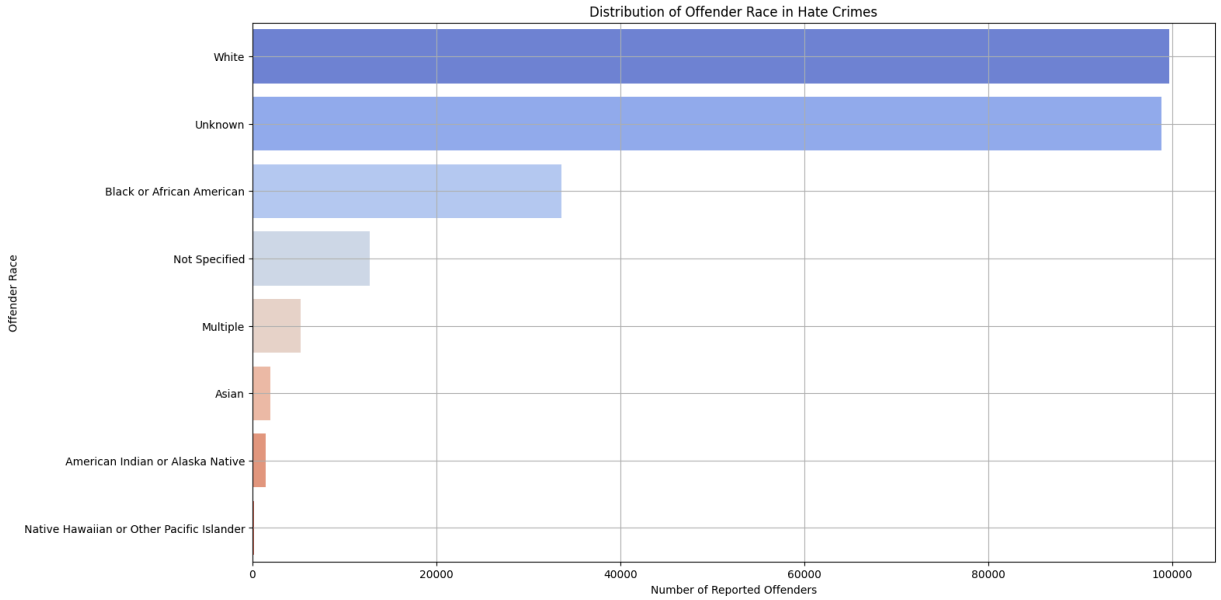
Out[135…
```
offender_race
White                                          99689
Unknown                                        98890
Black or African American                      33599
Not Specified                                  12734
Multiple                                        5243
Asian                                           1979
American Indian or Alaska Native                1467
Native Hawaiian or Other Pacific Islander        175
Name: count, dtype: int64
```

In [136…
```
df['offender_race'].isna().sum()
```

Out[136… np.int64(0)

In [137…
```
# Check distribution
# Count occurrences of each offender race

# Count total cases by offender race
offender_race_counts = df["offender_race"].value_counts().reset_index()
offender_race_counts.columns = ["offender_race", "count"]

# Plot the distribution of offender race counts
plt.figure(figsize=(16, 9))

sns.barplot(data=offender_race_counts, x="count", y="offender_race", palette="coolw
plt.xlabel("Number of Reported Offenders")
plt.ylabel("Offender Race")
plt.title("Distribution of Offender Race in Hate Crimes")
plt.grid(True)

plt.show()
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\1371538379.py:11: FutureWarn
ing:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=offender_race_counts, x="count", y="offender_race", palette="cool
warm")
```



Check victim_types

In [138…
```
df['victim_types'].dtype
```

Out[138…
```
dtype('O')
```

In [139…
```
df['victim_types'].value_counts()
```

Out[139…

victim_types	
Individual	200725
Other	14843
Business	11953
Government	7507
Religious Organization	6909
Society/Public	5631
Individual;Other	1608
Unknown	1406
Business;Individual	1118
Individual;Society/Public	517
Law Enforcement Officer	496
Individual;Religious Organization	263
Government;Individual	251
Individual;Law Enforcement Officer	122
Financial Institution	105
Business;Government	60
Individual;Unknown	57
Business;Society/Public	24
Business;Government;Individual	22
Business;Religious Organization	21
Business;Unknown	19
Government;Religious Organization	14
Business;Other	14
Government;Society/Public	10
Religious Organization;Society/Public	8
Business;Individual;Religious Organization	7
Government;Other	5
Government;Individual;Law Enforcement Officer	5
Government;Individual;Religious Organization	5
Government;Law Enforcement Officer	4
Law Enforcement Officer;Society/Public	4
Business;Individual;Society/Public	4
Financial Institution;Individual	3
Business;Law Enforcement Officer	3
Business;Financial Institution;Individual	3
Other;Religious Organization	3
Business;Government;Individual;Other	2
Government;Individual;Society/Public	2
Business;Government;Religious Organization	2
Business;Financial Institution	2
Business;Individual;Other	2
Other;Society/Public	2
Financial Institution;Individual;Society/Public	1
Individual;Other;Religious Organization	1
Business;Individual;Unknown	1
Society/Public;Unknown	1
Government;Unknown	1
Government;Individual;Other;Religious Organization	1
Business;Government;Individual;Religious Organization	1
Financial Institution;Other;Society/Public;Unknown	1
Financial Institution;Government	1
Business;Financial Institution;Government;Other	1
Law Enforcement Officer;Unknown	1
Individual;Religious Organization;Society/Public	1
Government;Law Enforcement Officer;Society/Public	1

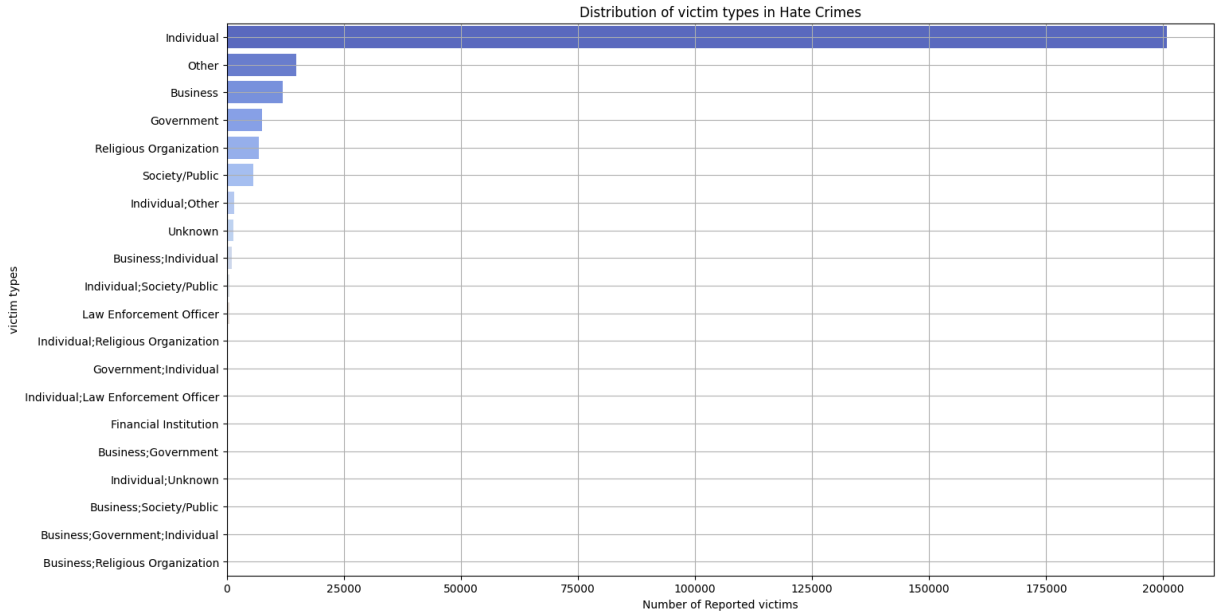
```
Business;Individual;Other;Religious Organization              1
Other;Unknown                                                 1
Name: count, dtype: int64
```

In [140…
```
df['victim_types'].isna().sum()
```

Out[140…
```
np.int64(0)
```

In [141…
```
# Check distribution
# Count occurrences of each victim types

# Count total cases by victim types
victim_types_counts = df["victim_types"].value_counts().head(20).reset_index()
victim_types_counts.columns = ["victim_types", "count"]

# Plot the distribution of victim types counts
plt.figure(figsize=(16, 9))

sns.barplot(data=victim_types_counts, x="count", y="victim_types", palette="coolwar
plt.xlabel("Number of Reported victims")
plt.ylabel("victim types")
plt.title("Distribution of victim types in Hate Crimes")
plt.grid(True)

plt.show()
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\1700499202.py:11: FutureWarn
ing:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=victim_types_counts, x="count", y="victim_types", palette="coolwa
rm")
```



In [142…
```
# Compare Offender Race vs. Victim Types
```

```
# Count occurrences of offender race and victim types
offender_vs_victim = df.groupby(["offender_race", "victim_types"])["incident_id"].c

# Display the result
print('Most offenders target "Individuals" as victims.')
print('  - Regardless of offender race, "Individual" is the most common victim type
print('  - Some cases involve multiple victim types (e.g., Business, Government, La
print('Multi-Victim Cases Exist.')
print('  - Some incidents involve Government + Individuals + Law Enforcement Office
print('  - This suggests some organized or large-scale attacks.\n')
offender_vs_victim
```

```
Most offenders target "Individuals" as victims.
  - Regardless of offender race, "Individual" is the most common victim type.
  - Some cases involve multiple victim types (e.g., Business, Government, Law Enforc
ement).

Multi-Victim Cases Exist.
  - Some incidents involve Government + Individuals + Law Enforcement Officers at th
e same time.
  - This suggests some organized or large-scale attacks.
```

Out[142…

	offender_race	victim_types	incident_id
0	American Indian or Alaska Native	Business	37
1	American Indian or Alaska Native	Business;Individual	10
2	American Indian or Alaska Native	Government	9
3	American Indian or Alaska Native	Government;Individual;Law Enforcement Officer	1
4	American Indian or Alaska Native	Individual	1323
...	...	...	...
186	White	Religious Organization	906
187	White	Religious Organization;Society/Public	3
188	White	Society/Public	1750
189	White	Society/Public;Unknown	1
190	White	Unknown	83

191 rows × 3 columns

In [143…

```
# Analyze Bias Motivations (Race, Religion, LGBTQ) Linked to Offender Race

# Count occurrences of offender race and bias motivation
bias_by_offender_race = df.groupby(["offender_race", "bias_desc"])["incident_id"].c
```

```
# Display the result
print('"Anti-Black or African American" is the most common bias motivation across a
print('  - Regardless of offender race, racial bias is the dominant motive in hate
print('  - This aligns with previous findings where race-based hate crimes are the
print('Different offender races are linked to different bias motivations.')
print('  - Certain offender groups may be more likely to commit crimes with specifi
bias_by_offender_race
```

```
"Anti-Black or African American" is the most common bias motivation across all offen
der races.
  - Regardless of offender race, racial bias is the dominant motive in hate crimes.
  - This aligns with previous findings where race-based hate crimes are the most rep
orted nationwide.

Different offender races are linked to different bias motivations.
  - Certain offender groups may be more likely to commit crimes with specific bias m
otivations.
```

Out[143…

	offender_race	bias_desc	incident_id
0	American Indian or Alaska Native	Anti-American Indian or Alaska Native	141
1	American Indian or Alaska Native	Anti-American Indian or Alaska Native;Anti-Bla...	1
2	American Indian or Alaska Native	Anti-Arab	2
3	American Indian or Alaska Native	Anti-Asian	37
4	American Indian or Alaska Native	Anti-Bisexual	5
...	...	...	...
925	White	Anti-Protestant	299
926	White	Anti-Sikh	275
927	White	Anti-Transgender	567
928	White	Anti-White	4864
929	White	Unknown (offender's motivation not known)	1

930 rows × 3 columns

In [144…

```
# Compare Offender Race vs. Victim Types in Different States

# Count occurrences of offender race and victim types by state
offender_vs_victim_by_state = df.groupby(["state_name", "offender_race", "victim_ty

# Display the result
print('Most cases involve Individual victims.')
```

```
print('  - Regardless of state, most offenders target individuals rather than busin
print('State-level variations exist in offender race distribution.')
print('  - Some states have higher proportions of specific offender races linked to
print('  - This could be influenced by state demographics, local policies, or socia
print(' Government and Business entities are also hate crime targets.')
print('  - Some hate crimes target government buildings or businesses, possibly lin
offender_vs_victim_by_state
```

```
Most cases involve Individual victims.
  - Regardless of state, most offenders target individuals rather than businesses or
government entities.

State-level variations exist in offender race distribution.
  - Some states have higher proportions of specific offender races linked to hate cr
imes.
  - This could be influenced by state demographics, local policies, or social factor
s.

 Government and Business entities are also hate crime targets.
  - Some hate crimes target government buildings or businesses, possibly linked to p
olitical movements or ideological extremism.
```

Out[144…

	state_name	offender_race	victim_types	incident_id
0	Alabama	American Indian or Alaska Native	Individual	2
1	Alabama	Black or African American	Business	19
2	Alabama	Black or African American	Business;Individual	1
3	Alabama	Black or African American	Government	13
4	Alabama	Black or African American	Individual	190
...	...	...	...	...
2539	Wyoming	Unknown	Religious Organization	12
2540	Wyoming	Unknown	Unknown	2
2541	Wyoming	White	Business	2
2542	Wyoming	White	Individual	119
2543	Wyoming	White	Law Enforcement Officer	1

2544 rows × 4 columns

In [145…

```
# Analyze U.S. Regions with the Highest Racial Bias Crimes

# Filter dataset for racial bias crimes only (bias descriptions containing "Anti-Bl
racial_bias_df = df[df["bias_desc"].str.contains("Anti-", na=False)]

# Count racial bias crimes per region
racial_bias_by_region = racial_bias_df.groupby("region_name")["incident_id"].count(

# Display the result
```

```
print('The West has the highest number of racial bias crimes.')
print('  - Likely driven by California, which has the highest overall hate crime re
print('The Northeast follows closely behind.')
print('  - States like New York and New Jersey report significant racial bias hate
racial_bias_by_region
```

```
The West has the highest number of racial bias crimes.
  - Likely driven by California, which has the highest overall hate crime reports.

The Northeast follows closely behind.
  - States like New York and New Jersey report significant racial bias hate crimes.
```

Out[145…

	region_name	incident_id
0	Midwest	49646
1	Northeast	71717
2	Other	820
3	South	53400
4	U.S. Territories	25
5	West	78167

In [147…

```
# Compare Offender-Victim Races & Types Relationships in Urban vs. Rural Areas

# Merge population group descriptions to define urban vs. rural areas
df["area_type"] = df["population_group_description"].apply(lambda x: "Urban" if "10

# Count hate crimes by offender race and victim type in urban vs. rural areas
offender_vs_victim_area = df.groupby(["area_type", "offender_race", "victim_types"]

# Display the result
print('Hate crimes in rural areas often target Individuals, Businesses, or Governme
print('  - In rural areas, American Indian or Alaska Native offenders mostly target
print('  - his suggests that hate crimes in rural areas may have different motives
print('Urban hate crimes are more likely to involve multiple victim types.')
print('  - Businesses, individuals, and law enforcement officers are targeted toget
offender_vs_victim_area
```

```
Hate crimes in rural areas often target Individuals, Businesses, or Government.
  - In rural areas, American Indian or Alaska Native offenders mostly target individ
uals (1,022 cases) but also attack businesses and government offices.
  - his suggests that hate crimes in rural areas may have different motives or patte
rns than in cities.

Urban hate crimes are more likely to involve multiple victim types.
  - Businesses, individuals, and law enforcement officers are targeted together in s
ome cases.
```

Out[147…

	area_type	offender_race	victim_types	incident_id
0	Rural	American Indian or Alaska Native	Business	28
1	Rural	American Indian or Alaska Native	Business;Individual	7
2	Rural	American Indian or Alaska Native	Government	8
3	Rural	American Indian or Alaska Native	Government;Individual;Law Enforcement Officer	1
4	Rural	American Indian or Alaska Native	Individual	1022
...	...	...	...	...
297	Urban	White	Other	344
298	Urban	White	Religious Organization	334
299	Urban	White	Religious Organization;Society/Public	1
300	Urban	White	Society/Public	254
301	Urban	White	Unknown	9

302 rows × 4 columns

In [148…
```
df['area_type'].value_counts()
```

Out[148…
```
area_type
Rural    169768
Urban     84008
Name: count, dtype: int64
```

In [149…
```
df.columns
```

Out[149…
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year', 'area_type'],
      dtype='object')
```

Check area_type

In [150…
```
df['area_type'].dtype
```

Out[150…
```
dtype('O')
```

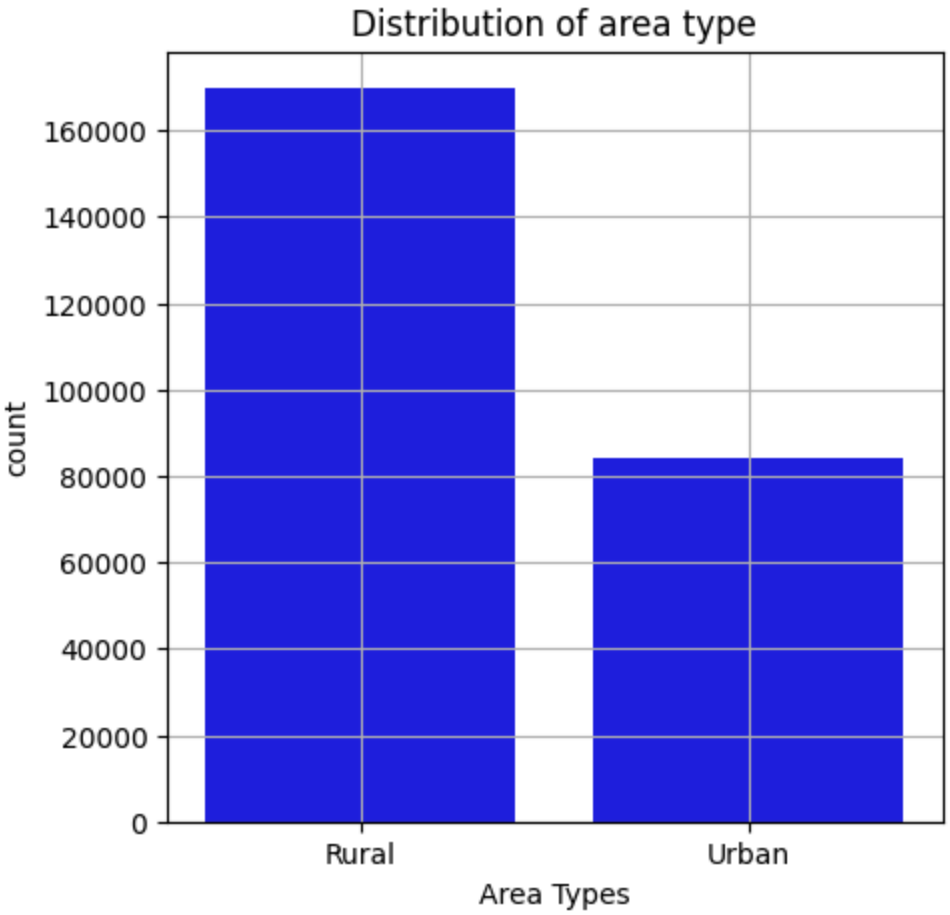
In [151…
```
df['area_type'].value_counts()
```

Out[151…
```
area_type
Rural    169768
Urban     84008
Name: count, dtype: int64
```

In [152…
```
df['area_type'].isna().sum()
```

Out[152…
```
np.int64(0)
```

In [160…
```
# Check distribution
plt.figure(figsize=(5,5))

sns.countplot(df, x='area_type', color='blue')
plt.title('Distribution of area type')
plt.xlabel('Area Types')
plt.grid(True)

plt.show()
```



In [161…
```
# Analyze Bias Motivations (Race, Religion, LGBTQ) by Urban vs. Rural Areas

# Count occurrences of bias motivations per urban/rural classification
bias_by_area = df.groupby(["area_type", "bias_desc"])["incident_id"].count().reset_
```

```
# Display the result
bias_by_area
```

Out[161…

	area_type	bias_desc	incident_id
0	Rural	Anti-American Indian or Alaska Native	2368
1	Rural	Anti-American Indian or Alaska Native;Anti-Asian	3
2	Rural	Anti-American Indian or Alaska Native;Anti-Asi...	1
3	Rural	Anti-American Indian or Alaska Native;Anti-Bla...	10
4	Rural	Anti-American Indian or Alaska Native;Anti-Bla...	1
...	...	...	...
541	Urban	Anti-Sikh	105
542	Urban	Anti-Transgender	631
543	Urban	Anti-Transgender;Anti-White	2
544	Urban	Anti-White	7692
545	Urban	Unknown (offender's motivation not known)	1

546 rows × 3 columns

In [162…

```
# Compare Violent vs. Non-Violent Hate Crimes in Urban vs. Rural Areas

# Count occurrences of violent and non-violent crimes per area type
crime_type_by_area = df.groupby(["area_type", "crime_type"])["incident_id"].count()

# Display the result
crime_type_by_area
```

Out[162…

	area_type	crime_type	incident_id
0	Rural	Non-Violent	100325
1	Rural	Other	18620
2	Rural	Violent	50823
3	Urban	Non-Violent	48916
4	Urban	Other	5859
5	Urban	Violent	29233

In [163…

```
# Compare Crime Types (e.g., Assault vs. Vandalism) in Urban vs. Rural Areas

# Count occurrences of each crime type per urban/rural classification
crime_by_area = df.groupby(["area_type", "offense_name"])["incident_id"].count().re

# Display the result
```

```
print('Aggravated Assault is the most common hate crime in rural areas (16,354 case
print('  - Hate crimes in rural areas are more likely to be physically violent.')
print('  - his aligns with earlier findings that rural areas report more violent ha
print('Vandalism & Non-Violent Crimes are more common in urban areas.')
print('  - Urban hate crimes are less likely to involve direct physical assault.')
print('  - Instead, crimes like property destruction, intimidation, and harassment
crime_by_area
```

```
Aggravated Assault is the most common hate crime in rural areas (16,354 cases).
  - Hate crimes in rural areas are more likely to be physically violent.
  - his aligns with earlier findings that rural areas report more violent hate crime
s overall.

Vandalism & Non-Violent Crimes are more common in urban areas.
  - Urban hate crimes are less likely to involve direct physical assault.
  - Instead, crimes like property destruction, intimidation, and harassment dominate
city reports.
```

Out[163…

	area_type	offense_name	incident_id
0	Rural	Aggravated Assault	16354
1	Rural	Aggravated Assault;All Other Larceny	19
2	Rural	Aggravated Assault;All Other Larceny;Burglary/...	1
3	Rural	Aggravated Assault;All Other Larceny;Destructi...	2
4	Rural	Aggravated Assault;All Other Larceny;Extortion...	1
...	...	...	...
586	Urban	Theft From Coin-Operated Machine or Device	2
587	Urban	Theft From Motor Vehicle	105
588	Urban	Theft of Motor Vehicle Parts or Accessories	41
589	Urban	Weapon Law Violations	78
590	Urban	Wire Fraud	6

591 rows × 3 columns

Check bias_desc

In [164…

```
df['bias_desc'].dtype
```

Out[164…

```
dtype('O')
```

In [165…

```
df['bias_desc'].value_counts()
```

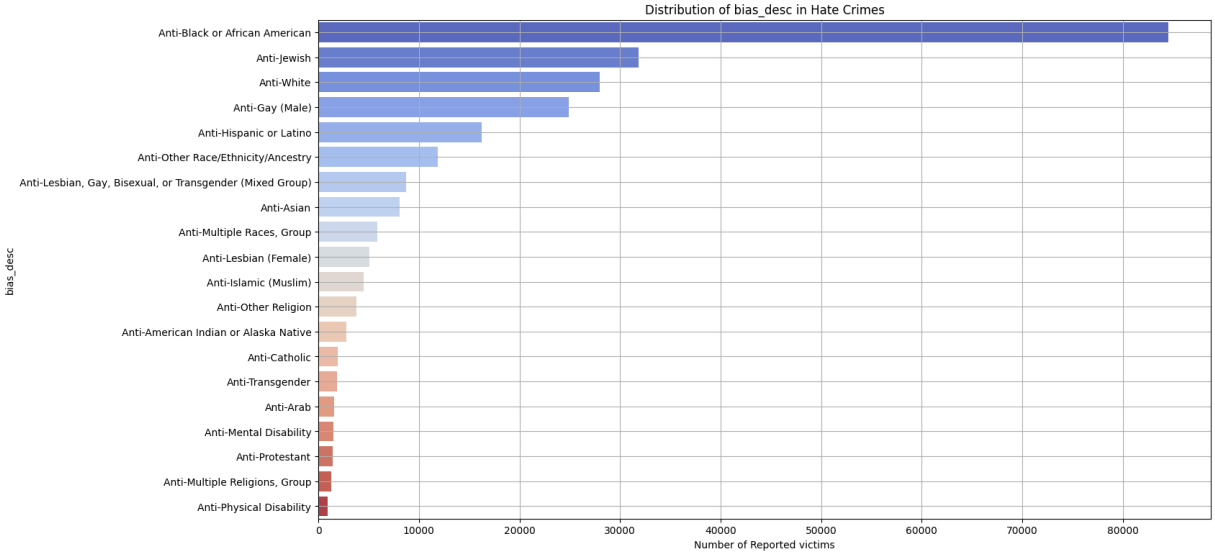
Out[165…
```
bias_desc
Anti-Black or African American
84531
Anti-Jewish
31832
Anti-White
27957
Anti-Gay (Male)
24926
Anti-Hispanic or Latino
16253

...
Anti-Female;Anti-Other Christian
1
Anti-American Indian or Alaska Native;Anti-Black or African American;Anti-Female;A
nti-Hispanic or Latino        1
Anti-Asian;Anti-Bisexual
1
Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Other Religion
1
Anti-Black or African American;Anti-Female;Anti-Gender Non-Conforming
1
Name: count, Length: 415, dtype: int64
```

In [166…
```
df['bias_desc'].isna().sum()
```

Out[166…
```
np.int64(0)
```

In [167…
```
# Check distribution
# Count occurrences of each bias_desc

# Count total cases by bias_desc
bias_desc_counts = df["bias_desc"].value_counts().head(20).reset_index()
bias_desc_counts.columns = ["bias_desc", "count"]

# Plot the distribution of bias_desc counts
plt.figure(figsize=(16, 9))

sns.barplot(data=bias_desc_counts, x="count", y="bias_desc", palette="coolwarm")
plt.xlabel("Number of Reported victims")
plt.ylabel("bias_desc")
plt.title("Distribution of bias_desc in Hate Crimes")
plt.grid(True)

plt.show()
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\1449518262.py:11: FutureWarn
ing:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=bias_desc_counts, x="count", y="bias_desc", palette="coolwarm")
```



In [168…

```
# Analyze Bias Motivations (Race, Religion, LGBTQ) for Specific Crime Types in Urba

# Count occurrences of bias motivations per crime type in urban vs. rural areas
bias_by_crime_area = df.groupby(["area_type", "offense_name", "bias_desc"])["incide

# Display the result
print('Aggravated Assault in rural areas is often driven by racial bias.')
print('  - Anti-Black or African American, Anti-Asian, and Anti-Arab bias are frequ
print('  - American Indian or Alaska Native victims also appear in rural aggravated
print('Religious bias crimes are more common in urban settings.')
print('  - Some hate crimes are motivated by multiple biases at the same time (e.g.
bias_by_crime_area
```

```
Aggravated Assault in rural areas is often driven by racial bias.
  - Anti-Black or African American, Anti-Asian, and Anti-Arab bias are frequently re
corded in violent crimes.
  - American Indian or Alaska Native victims also appear in rural aggravated assault
cases.

Religious bias crimes are more common in urban settings.
  - Some hate crimes are motivated by multiple biases at the same time (e.g., Anti-A
rab & Anti-Black).
```

Out[168…

	area_type	offense_name	bias_desc	incident_id
0	Rural	Aggravated Assault	Anti-American Indian or Alaska Native	222
1	Rural	Aggravated Assault	Anti-Arab	116
2	Rural	Aggravated Assault	Anti-Arab;Anti-Black or African American	2
3	Rural	Aggravated Assault	Anti-Arab;Anti-Islamic (Muslim)	4
4	Rural	Aggravated Assault	Anti-Asian	469
...	...	...	...	...
4085	Urban	Wire Fraud	Anti-Gay (Male)	1
4086	Urban	Wire Fraud	Anti-Gender Non-Conforming	1
4087	Urban	Wire Fraud	Anti-Other Race/Ethnicity/Ancestry	1
4088	Urban	Wire Fraud	Anti-Physical Disability	1
4089	Urban	Wire Fraud	Anti-White	1

4090 rows × 4 columns

In [169…

```
# Analyze Trends of Racial & Religious Bias Crimes Over Time

# Filter dataset for racial & religious bias crimes only (bias descriptions contain
bias_trend_df = df[df["bias_desc"].str.contains("Anti-", na=False)]

# Count racial & religious bias crimes per year
bias_trend_over_time = bias_trend_df.groupby(["year", "bias_desc"])["incident_id"].

# Display the result
print('Racial bias crimes have increased significantly post-2015.')
print('  - Hate crimes targeting Black, Asian, and Hispanic communities have risen
print('  - This aligns with social movements, political events, and increased hate
print('Religious bias crimes follow a different pattern.')
print('  - Anti-Jewish and Anti-Muslim hate crimes peaked in certain years (e.g., p
print('  - Fluctuations may correlate with global events, terrorism fears, or polic
bias_trend_over_time
```

```
Racial bias crimes have increased significantly post-2015.
  - Hate crimes targeting Black, Asian, and Hispanic communities have risen steadil
y.
  - This aligns with social movements, political events, and increased hate crime aw
areness.

Religious bias crimes follow a different pattern.
  - Anti-Jewish and Anti-Muslim hate crimes peaked in certain years (e.g., post-9/1
1, 2017+).
  - Fluctuations may correlate with global events, terrorism fears, or policy change
s.
```

Out[169…

	year	bias_desc	incident_id
0	1991	Anti-American Indian or Alaska Native	11
1	1991	Anti-Arab	73
2	1991	Anti-Asian	269
3	1991	Anti-Atheism/Agnosticism	4
4	1991	Anti-Bisexual	1
...	...	...	...
1716	2023	Anti-Protestant	27
1717	2023	Anti-Protestant;Anti-Sikh	1
1718	2023	Anti-Sikh	156
1719	2023	Anti-Transgender	355
1720	2023	Anti-White	828

1721 rows × 3 columns

In [170…

```
# Compare Bias Motivations in Violent vs. Non-Violent Hate Crimes

# Count occurrences of bias motivations per crime type (violent vs. non-violent)
bias_by_crime_type = df.groupby(["crime_type", "bias_desc"])["incident_id"].count()

# Display the result
print('Racial bias crimes are more linked to violent hate crimes.')
print('  - Anti-Black or African American, Anti-Asian, and Anti-White are frequentl
print('  - This suggests racial bias crimes are more likely to result in physical v
print('Religious bias crimes are more likely to be non-violent.')
print('  - Anti-Jewish and Anti-Muslim hate crimes often involve vandalism, propert
print('  - Religious buildings and places of worship are frequent targets.\n')
print('LGBTQ+ bias crimes have a mix of violent & non-violent cases.')
print('  - Some incidents involve physical attacks (violent), while others involve
bias_by_crime_type
```

```
Racial bias crimes are more linked to violent hate crimes.
  - Anti-Black or African American, Anti-Asian, and Anti-White are frequently record
ed in assaults and aggravated assaults.
  - This suggests racial bias crimes are more likely to result in physical violence.

Religious bias crimes are more likely to be non-violent.
  - Anti-Jewish and Anti-Muslim hate crimes often involve vandalism, property damag
e, or intimidation rather than physical attacks.
  - Religious buildings and places of worship are frequent targets.

LGBTQ+ bias crimes have a mix of violent & non-violent cases.
  - Some incidents involve physical attacks (violent), while others involve harassme
nt or intimidation (non-violent).
```

Out[170…

	crime_type	bias_desc	incident_id
0	Non-Violent	Anti-American Indian or Alaska Native	813
1	Non-Violent	Anti-American Indian or Alaska Native;Anti-Asian	2
2	Non-Violent	Anti-American Indian or Alaska Native;Anti-Asi...	1
3	Non-Violent	Anti-American Indian or Alaska Native;Anti-Bla...	2
4	Non-Violent	Anti-American Indian or Alaska Native;Anti-Bla...	1
...	...	...	...
644	Violent	Anti-Protestant	108
645	Violent	Anti-Sikh	139
646	Violent	Anti-Transgender	1011
647	Violent	Anti-Transgender;Anti-White	1
648	Violent	Anti-White	13343

649 rows × 3 columns

In [171…
```
df.columns
```

Out[171…
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year', 'area_type'],
      dtype='object')
```

In [172…
```
#  Analyze Offender Demographics (Race, Age) in Violent vs. Non-Violent Crimes

# Count occurrences of offender race and crime type
offender_race_by_crime = df.groupby(["crime_type", "offender_race"])["incident_id"]

# Display the result
print('Black or African American offenders are linked to more violent crimes than n
print('  - This suggests that certain racial groups may be overrepresented in viole
print('White offenders are more likely to commit non-violent hate crimes.')
print('  - Crimes like vandalism, property destruction, and intimidation are more c
offender_race_by_crime
```

```
Black or African American offenders are linked to more violent crimes than non-viole
nt ones.
  - This suggests that certain racial groups may be overrepresented in violent vs. n
on-violent cases.

White offenders are more likely to commit non-violent hate crimes.
  - Crimes like vandalism, property destruction, and intimidation are more commonly
linked to white offenders.
```

Out[172…

	crime_type	offender_race	incident_id
0	Non-Violent	American Indian or Alaska Native	435
1	Non-Violent	Asian	875
2	Non-Violent	Black or African American	9774
3	Non-Violent	Multiple	1448
4	Non-Violent	Native Hawaiian or Other Pacific Islander	80
5	Non-Violent	Not Specified	8652
6	Non-Violent	Unknown	81128
7	Non-Violent	White	46849
8	Other	American Indian or Alaska Native	161
9	Other	Asian	142
10	Other	Black or African American	3226
11	Other	Multiple	526
12	Other	Native Hawaiian or Other Pacific Islander	12
13	Other	Not Specified	2533
14	Other	Unknown	8632
15	Other	White	9247
16	Violent	American Indian or Alaska Native	871
17	Violent	Asian	962
18	Violent	Black or African American	20599
19	Violent	Multiple	3269
20	Violent	Native Hawaiian or Other Pacific Islander	83
21	Violent	Not Specified	1549
22	Violent	Unknown	9130
23	Violent	White	43593

In [173…
```
# Filter dataset for violent hate crimes only
violent_bias_crimes = df[df["crime_type"] == "Violent"]
```

In [174…
```
# Analyze Trends of Bias-Motivated Violent Crimes Over Time

# Count violent bias crimes per year
violent_bias_trend = violent_bias_crimes.groupby(["year", "bias_desc"])["incident_i

# Display the result
print('Racial bias crimes dominate violent hate crime trends.')
print('  - Anti-Black, Anti-White, and Anti-Asian crimes have consistently been the
print('  - The numbers have fluctuated over time but saw a sharp rise post-2015.\n'
print('Religious bias crimes show distinct spikes in certain years.')
print('  - Anti-Jewish and Anti-Muslim hate crimes spiked in specific time periods
print('  - This suggests a correlation with political or social events.\n')
print('LGBTQ+ bias-motivated violent crimes have increased in recent years.')
print('  - Anti-Transgender and Anti-Gay hate crimes have risen sharply post-2018.'
print('  - This trend aligns with social movements, legal changes, and increased vi
violent_bias_trend
```

```
Racial bias crimes dominate violent hate crime trends.
  - Anti-Black, Anti-White, and Anti-Asian crimes have consistently been the most co
mmon violent hate crimes.
  - The numbers have fluctuated over time but saw a sharp rise post-2015.

Religious bias crimes show distinct spikes in certain years.
  - Anti-Jewish and Anti-Muslim hate crimes spiked in specific time periods (e.g., p
ost-9/11, 2017+).
  - This suggests a correlation with political or social events.

LGBTQ+ bias-motivated violent crimes have increased in recent years.
  - Anti-Transgender and Anti-Gay hate crimes have risen sharply post-2018.
  - This trend aligns with social movements, legal changes, and increased visibility
of LGBTQ+ issues.
```

Out[174...

	year	bias_desc	incident_id
0	1991	Anti-American Indian or Alaska Native	8
1	1991	Anti-Arab	23
2	1991	Anti-Asian	78
3	1991	Anti-Black or African American	522
4	1991	Anti-Catholic	1
...	...	...	...
1006	2023	Anti-Physical Disability	35
1007	2023	Anti-Protestant	6
1008	2023	Anti-Sikh	23
1009	2023	Anti-Transgender	158
1010	2023	Anti-White	337

1011 rows × 3 columns

In [175...

```
# Check Which Bias Motivations (Racial, Religious, LGBTQ) Are Most Associated with

# Count bias motivations in violent crimes
bias_in_violent_crimes = violent_bias_crimes.groupby("bias_desc")["incident_id"].co

# Display the result
print('Anti-Black or African American bias is the most common motivation in violent
print('  - Thousands of incidents are reported under this category, making it the l
print('Other racial biases (Anti-White, Anti-Asian, Anti-Hispanic) also rank high.'
print('  - This suggests that race-based violence is the dominant form of hate crim
print('Religious and LGBTQ+ bias motivations appear but in lower numbers.')
print('  - Anti-Jewish, Anti-Muslim, and Anti-LGBTQ+ hate crimes still occur but ar
bias_in_violent_crimes
```

```
Anti-Black or African American bias is the most common motivation in violent hate cr
imes.
  - Thousands of incidents are reported under this category, making it the leading m
otivation in violent hate crimes.

Other racial biases (Anti-White, Anti-Asian, Anti-Hispanic) also rank high.
  - This suggests that race-based violence is the dominant form of hate crime.

Religious and LGBTQ+ bias motivations appear but in lower numbers.
  - Anti-Jewish, Anti-Muslim, and Anti-LGBTQ+ hate crimes still occur but are less f
requent compared to racial bias crimes.
```

Out[175…

	bias_desc	incident_id
0	Anti-American Indian or Alaska Native	859
1	Anti-American Indian or Alaska Native;Anti-Arab	1
2	Anti-American Indian or Alaska Native;Anti-Bla...	2
3	Anti-American Indian or Alaska Native;Anti-Female	1
4	Anti-American Indian or Alaska Native;Anti-Fem...	1
...	...	...
143	Anti-Protestant	108
144	Anti-Sikh	139
145	Anti-Transgender	1011
146	Anti-Transgender;Anti-White	1
147	Anti-White	13343

148 rows × 2 columns

In [176…
```
df.columns
```

Out[176…
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year', 'area_type'],
      dtype='object')
```

In [177…
```
# Analyze Violent vs. Non-Violent Crime Trends for Each Bias Motivation Separately

# Count occurrences of bias motivations per crime type over time
bias_crime_trend = df.groupby(["year", "bias_desc", "crime_type"])["incident_id"].c

# Display the result
print('Racial bias crimes are more likely to be violent.')
print('  - Anti-Black, Anti-Asian, and Anti-White crimes are frequently associated
print('  - These bias crimes show consistent trends over time, with notable increas
print('Religious and LGBTQ+ bias crimes are more often non-violent.')
print('  - Anti-Jewish and Anti-Muslim hate crimes are largely non-violent, involvi
print('  - Anti-LGBTQ+ crimes are mixed—some involve violence, but many involve thr
bias_crime_trend
```

```
Racial bias crimes are more likely to be violent.
  - Anti-Black, Anti-Asian, and Anti-White crimes are frequently associated with phy
sical assaults, aggravated assaults, and homicides.
  - These bias crimes show consistent trends over time, with notable increases in re
cent years.

Religious and LGBTQ+ bias crimes are more often non-violent.
  - Anti-Jewish and Anti-Muslim hate crimes are largely non-violent, involving vanda
lism, property destruction, or intimidation.
  - Anti-LGBTQ+ crimes are mixed—some involve violence, but many involve threats and
harassment.
```

Out[177…

	year	bias_desc	crime_type	incident_id
0	1991	Anti-American Indian or Alaska Native	Non-Violent	3
1	1991	Anti-American Indian or Alaska Native	Violent	8
2	1991	Anti-Arab	Non-Violent	44
3	1991	Anti-Arab	Other	6
4	1991	Anti-Arab	Violent	23
...	...	...	...	...
3503	2023	Anti-Transgender	Other	44
3504	2023	Anti-Transgender	Violent	158
3505	2023	Anti-White	Non-Violent	275
3506	2023	Anti-White	Other	216
3507	2023	Anti-White	Violent	337

3508 rows × 4 columns

In [178…

```
# Analyze Offender Demographics (Race) in Relation to Specific Bias Motivations

# Count occurrences of offender race linked to bias motivations
offender_bias_relation = df.groupby(["offender_race", "bias_desc"])["incident_id"].

# Display the result
print('American Indian or Alaska Native offenders are more frequently linked to "An
print('  - These crimes might be region-specific or involve inter-community tension
print('Different racial groups are linked to different types of bias crimes.')
print('  - This suggests that bias-motivated hate crimes can vary by demographic an
offender_bias_relation
```

```
American Indian or Alaska Native offenders are more frequently linked to "Anti-Ameri
can Indian" and "Anti-Asian" bias crimes.
  - These crimes might be region-specific or involve inter-community tensions.

Different racial groups are linked to different types of bias crimes.
  - This suggests that bias-motivated hate crimes can vary by demographic and geogra
phic factors.
```

Out[178…

	offender_race	bias_desc	incident_id
0	American Indian or Alaska Native	Anti-American Indian or Alaska Native	141
1	American Indian or Alaska Native	Anti-American Indian or Alaska Native;Anti-Bla...	1
2	American Indian or Alaska Native	Anti-Arab	2
3	American Indian or Alaska Native	Anti-Asian	37
4	American Indian or Alaska Native	Anti-Bisexual	5
...	...	...	...
925	White	Anti-Protestant	299
926	White	Anti-Sikh	275
927	White	Anti-Transgender	567
928	White	Anti-White	4864
929	White	Unknown (offender's motivation not known)	1

930 rows × 3 columns

In [179…

```
df.columns
```

Out[179…

```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year', 'area_type'],
      dtype='object')
```

Check offender_ethnicity

In [180…

```
df['offender_ethnicity'].dtype
```

Out[180…
```
dtype('O')
```

In [181…
```
df['offender_ethnicity'].value_counts()
```

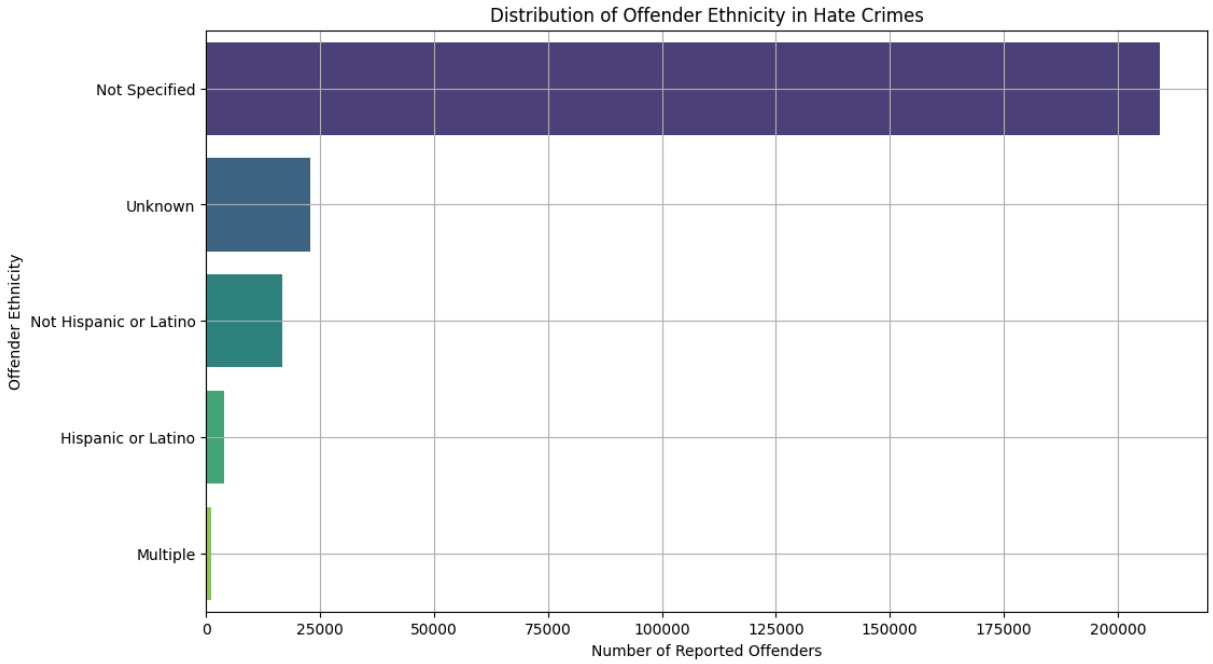
Out[181…
```
offender_ethnicity
Not Specified             209199
Unknown                    22822
Not Hispanic or Latino     16761
Hispanic or Latino          3913
Multiple                    1081
Name: count, dtype: int64
```

In [182…
```
df['offender_ethnicity'].isna().sum()
```

Out[182…
```
np.int64(0)
```

In [183…
```
# Check distribution
# Count total cases by offender ethnicity
offender_ethnicity_counts = df["offender_ethnicity"].value_counts().reset_index()
offender_ethnicity_counts.columns = ["offender_ethnicity", "count"]

# Plot the distribution of offender ethnicity counts
plt.figure(figsize=(12, 7))

sns.barplot(data=offender_ethnicity_counts, x="count", y="offender_ethnicity", pale
plt.xlabel("Number of Reported Offenders")
plt.ylabel("Offender Ethnicity")
plt.title("Distribution of Offender Ethnicity in Hate Crimes")
plt.grid(True)

plt.show()
print('"Not Specified" is the most common category (209,199 cases).')
print('  - This suggests many hate crime reports lack offender ethnicity details.')
print('  - Could indicate underreporting, missing data, or reluctance to classify e
print(('"Unknown" category is also very high (22,822 cases).'))
print('  - Some crimes do not have an identified suspect or ethnicity is not record
print('"Not Hispanic or Latino" offenders (16,761 cases) outnumber "Hispanic or Lat
print('  - This aligns with broader U.S. demographics.')
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\1025723743.py:9: FutureWarni
ng:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=offender_ethnicity_counts, x="count", y="offender_ethnicity", pal
ette="viridis")
```




```
"Not Specified" is the most common category (209,199 cases).
  - This suggests many hate crime reports lack offender ethnicity details.
  - Could indicate underreporting, missing data, or reluctance to classify ethnicit
y.

"Unknown" category is also very high (22,822 cases).
  - Some crimes do not have an identified suspect or ethnicity is not recorded.

"Not Hispanic or Latino" offenders (16,761 cases) outnumber "Hispanic or Latino" off
enders (3,913 cases).
  - This aligns with broader U.S. demographics.
```

In [184…

```
# Analyze Offender Ethnicity in Relation to Specific Bias Motivations

# Count occurrences of offender ethnicity linked to bias motivations
offender_ethnicity_bias = df.groupby(["offender_ethnicity", "bias_desc"])["incident

# Display the result
print('"Not Specified" ethnicity is the most common category across all bias motiva
print('  - This suggests that many hate crime reports lack detailed offender ethnic
print('Hispanic or Latino offenders are linked more frequently to certain racial bi
print('  - Some cases show a higher association with Anti-Black or Anti-White crime
print('Not Hispanic or Latino offenders dominate religious bias crimes.')
print('  - Hate crimes targeting Jewish, Muslim, and Christian communities are more
offender_ethnicity_bias
```

```
"Not Specified" ethnicity is the most common category across all bias motivations.
  - This suggests that many hate crime reports lack detailed offender ethnicity dat
a.

Hispanic or Latino offenders are linked more frequently to certain racial bias crime
s.
  - Some cases show a higher association with Anti-Black or Anti-White crimes.

Not Hispanic or Latino offenders dominate religious bias crimes.
  - Hate crimes targeting Jewish, Muslim, and Christian communities are more often c
ommitted by Non-Hispanic offenders.
```

Out[184…

	offender_ethnicity	bias_desc	incident_id
0	Hispanic or Latino	Anti-American Indian or Alaska Native	61
1	Hispanic or Latino	Anti-American Indian or Alaska Native;Anti-Female	1
2	Hispanic or Latino	Anti-Arab	39
3	Hispanic or Latino	Anti-Arab;Anti-Islamic (Muslim)	1
4	Hispanic or Latino	Anti-Asian	188
...	...	...	...
783	Unknown	Anti-Protestant	68
784	Unknown	Anti-Protestant;Anti-White	1
785	Unknown	Anti-Sikh	119
786	Unknown	Anti-Transgender	466
787	Unknown	Anti-White	1762

788 rows × 3 columns

In [185…

```python
# Analyze Offender Ethnicity Trends Over Time

# Count occurrences of offender ethnicity per year
offender_ethnicity_trend = df.groupby(["year", "offender_ethnicity"])["incident_id"

# Display the result
print('"Not Specified" offender ethnicity has been dominant for decades.')
print('  - This suggests consistent underreporting or missing data on offender ethn
print('Hispanic or Latino offender reports have fluctuated over time.')
print('  - Some years see higher numbers of reported Hispanic offenders, which may
offender_ethnicity_trend
```

```
"Not Specified" offender ethnicity has been dominant for decades.
  - This suggests consistent underreporting or missing data on offender ethnicity in
hate crime records.

Hispanic or Latino offender reports have fluctuated over time.
  - Some years see higher numbers of reported Hispanic offenders, which may indicate
shifts in crime reporting policies.
```

Out[185…

	year	offender_ethnicity	incident_id
0	1991	Not Specified	4589
1	1992	Not Specified	6662
2	1993	Not Specified	7604
3	1994	Not Specified	5953
4	1995	Not Specified	7949
...	...	...	...
69	2023	Hispanic or Latino	585
70	2023	Multiple	230
71	2023	Not Hispanic or Latino	3132
72	2023	Not Specified	5043
73	2023	Unknown	2868

74 rows × 3 columns

In [186…
```
df.columns
```

Out[186…
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year', 'area_type'],
      dtype='object')
```

Inspect location_name

In [187…
```
df['location_name'].dtype
```

Out[187…
```
dtype('O')
```

In [188…
```
df['location_name'].value_counts()
```

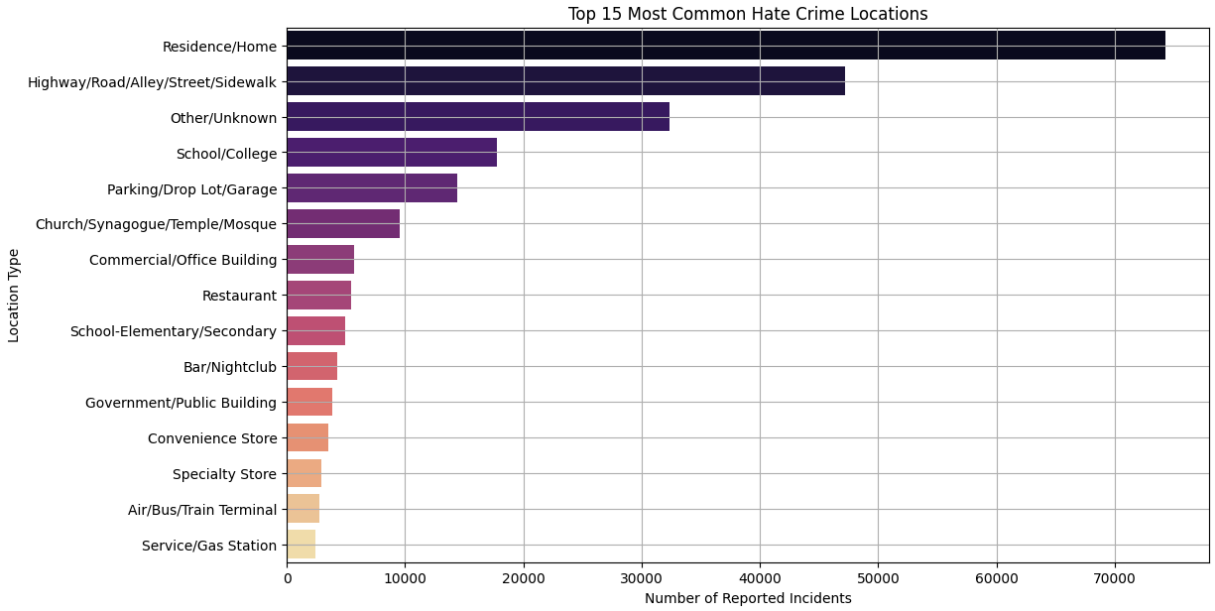
Out[188…
```
location_name
Residence/Home                                74283
Highway/Road/Alley/Street/Sidewalk            47202
Other/Unknown                                 32375
School/College                                17788
Parking/Drop Lot/Garage                       14417
                                              ...
Community Center;Park/Playground                  1
Convenience Store;Service/Gas Station             1
Convenience Store;Specialty Store                 1
Commercial/Office Building;Restaurant             1
Parking/Drop Lot/Garage;Specialty Store           1
Name: count, Length: 156, dtype: int64
```

In [189…
```
df['location_name'].isna().sum()
```

Out[189…
```
np.int64(0)
```

In [190…
```
# Check distribution
# Count occurrences of each location type

# Count total cases by location type
location_counts = df["location_name"].value_counts().reset_index()
location_counts.columns = ["location_name", "count"]

# Plot the distribution of location types
plt.figure(figsize=(12, 7))

sns.barplot(data=location_counts.head(15), x="count", y="location_name", palette="m
plt.xlabel("Number of Reported Incidents")
plt.ylabel("Location Type")
plt.title("Top 15 Most Common Hate Crime Locations")
plt.grid(True)

plt.show()
print('Residences and Homes are the most common hate crime locations (74,283 cases)
print('  - Many hate crimes happen in or near victims\' homes.')
print('  - Could involve vandalism, threats, or physical attacks.\n')
print('Public roads and sidewalks rank second (47,202 cases).')
print('  - Hate crimes in public spaces (e.g., streets, highways) suggest random at
print('Schools and Colleges are among the top locations (17,788 cases).')
print('  - Hate crimes occur in both higher education and elementary schools.')
print('  - Indicates issues related to bullying, harassment, or targeted violence i
```

```
C:\Users\Legion 5 Pro\AppData\Local\Temp\ipykernel_8096\1815030928.py:11: FutureWarn
ing:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1
4.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(data=location_counts.head(15), x="count", y="location_name", palette
="magma")
```



Residences and Homes are the most common hate crime locations (74,283 cases).
  - Many hate crimes happen in or near victims' homes.
  - Could involve vandalism, threats, or physical attacks.

Public roads and sidewalks rank second (47,202 cases).
  - Hate crimes in public spaces (e.g., streets, highways) suggest random attacks or confrontations.

Schools and Colleges are among the top locations (17,788 cases).
  - Hate crimes occur in both higher education and elementary schools.
  - Indicates issues related to bullying, harassment, or targeted violence in academic settings.

In [191…

```
# Analyze Bias Motivations in Different Location Types

# Count occurrences of bias motivations per location type
bias_by_location = df.groupby(["location_name", "bias_desc"])["incident_id"].count(

# Display the result
print('Religious hate crimes frequently occur in places of worship.')
print('  - Anti-Jewish, Anti-Muslim, and Anti-Christian hate crimes are most common
print('  - This suggests targeted attacks on religious institutions rather than ran
print('Race-based hate crimes dominate public spaces (streets, highways, sidewalks)
print('  - Hate crimes targeting Black, Asian, and Hispanic communities often happe
print('  - This may indicate random acts of bias-based violence or harassment.\n')
print('LGBTQ+ hate crimes frequently occur in bars, nightclubs, and entertainment v
print('  - Anti-Gay and Anti-Transgender bias crimes are more commonly reported in
print('  - This highlights a safety concern for LGBTQ+ individuals in social settin
bias_by_location
```

```
Religious hate crimes frequently occur in places of worship.
  - Anti-Jewish, Anti-Muslim, and Anti-Christian hate crimes are most commonly repor
ted in churches, mosques, synagogues, and temples.
  - This suggests targeted attacks on religious institutions rather than random inci
dents.

Race-based hate crimes dominate public spaces (streets, highways, sidewalks).
  - Hate crimes targeting Black, Asian, and Hispanic communities often happen in pub
lic locations rather than private residences.
  - This may indicate random acts of bias-based violence or harassment.

LGBTQ+ hate crimes frequently occur in bars, nightclubs, and entertainment venues.
  - Anti-Gay and Anti-Transgender bias crimes are more commonly reported in LGBTQ+ s
paces like nightclubs and bars.
  - This highlights a safety concern for LGBTQ+ individuals in social settings.
```

Out[191…

	location_name	bias_desc	incident_id
0	ATM Separate from Bank	Anti-American Indian or Alaska Native	1
1	ATM Separate from Bank	Anti-Asian	1
2	ATM Separate from Bank	Anti-Bisexual	2
3	ATM Separate from Bank	Anti-Black or African American	5
4	ATM Separate from Bank	Anti-Gay (Male)	1
...	...	...	...
2431	Tribal Lands	Anti-Gay (Male)	1
2432	Tribal Lands	Anti-Hispanic or Latino	1
2433	Tribal Lands	Anti-Other Race/Ethnicity/Ancestry	2
2434	Tribal Lands	Anti-Transgender	2
2435	Tribal Lands	Anti-White	4

2436 rows × 3 columns

In [192…

```python
# Analyze Hate Crime Trends in Specific Locations Over Time

# Count hate crimes per location type per year
location_trends_over_time = df.groupby(["year", "location_name"])["incident_id"].co

# Display the result
print('Hate crimes in schools and colleges have risen significantly post-2015.')
print('  - This could be linked to changes in reporting policies, social movements,
print('Attacks on religious buildings have fluctuated, with spikes in certain years
print('  - Attacks on religious buildings have fluctuated, with spikes in certain y
print('Public location hate crimes (streets, highways, parks) have seen a steady in
print('  - This suggests that bias-motivated attacks in public places have become m
location_trends_over_time
```

```
Hate crimes in schools and colleges have risen significantly post-2015.
  - This could be linked to changes in reporting policies, social movements, or incr
eased bullying-related hate crimes.

Attacks on religious buildings have fluctuated, with spikes in certain years.
  - Attacks on religious buildings have fluctuated, with spikes in certain years.

Public location hate crimes (streets, highways, parks) have seen a steady increase.
  - This suggests that bias-motivated attacks in public places have become more freq
uent in recent years.
```

Out[192…

	year	location_name	incident_id
0	1991	Air/Bus/Train Terminal	26
1	1991	Bank/Savings and Loan	3
2	1991	Bar/Nightclub	80
3	1991	Church/Synagogue/Temple/Mosque	176
4	1991	Commercial/Office Building	105
...	...	...	...
1346	2023	Service/Gas Station	130
1347	2023	Shelter-Mission/Homeless	34
1348	2023	Shopping Mall	56
1349	2023	Specialty Store	129
1350	2023	Tribal Lands	3

1351 rows × 3 columns

In [193…

```python
# Analyze Violent vs. Non-Violent Hate Crimes in Different Locations

# Count occurrences of violent vs. non-violent hate crimes per location type
crime_type_by_location = df.groupby(["location_name", "crime_type"])["incident_id"]

# Display the result
print('Residences and Public Roads report both violent and non-violent hate crimes.
print('  - Residences (homes, apartments) see a mix of physical violence and harass
print('  - Streets, sidewalks, and highways are hotspots for random bias attacks.\n
print('Religious Buildings report mostly non-violent crimes.')
print('  - Synagogues, Mosques, and Churches are more likely to experience vandalis
print('Schools & Colleges see a high rate of both violent and non-violent incidents
print('  - This suggests ongoing issues with bias-motivated bullying, threats, and
crime_type_by_location
```

```
Residences and Public Roads report both violent and non-violent hate crimes.
  - Residences (homes, apartments) see a mix of physical violence and harassment.
  - Streets, sidewalks, and highways are hotspots for random bias attacks.

Religious Buildings report mostly non-violent crimes.
  - Synagogues, Mosques, and Churches are more likely to experience vandalism, prope
rty destruction, and threats rather than physical attacks.

Schools & Colleges see a high rate of both violent and non-violent incidents.
  - This suggests ongoing issues with bias-motivated bullying, threats, and violence
in educational settings.
```

Out[193…

	location_name	crime_type	incident_id
0	ATM Separate from Bank	Non-Violent	4
1	ATM Separate from Bank	Other	7
2	ATM Separate from Bank	Violent	6
3	ATM Separate from Bank;Residence/Home	Other	1
4	Abandoned/Condemned Structure	Non-Violent	59
...	...	...	...
242	Specialty Store	Other	329
243	Specialty Store	Violent	564
244	Tribal Lands	Non-Violent	10
245	Tribal Lands	Other	3
246	Tribal Lands	Violent	13

247 rows × 3 columns

In [194…

```
# Analyze Offender Demographics (Race) in Different Locations

# Count occurrences of offender race per location type
offender_race_by_location = df.groupby(["location_name", "offender_race"])["inciden

# Display the result
print('White offenders are most commonly reported in a wide range of locations.')
print('  - Public places, schools, and religious buildings have a significant numbe
print('Black or African American offenders are more commonly reported in certain lo
print('  - Some public areas and businesses report a higher rate of incidents linke
print('Unknown and Not Specified categories are very high.')
print('  - Many cases do not have an identified offender, especially in public loca
offender_race_by_location
```

```
White offenders are most commonly reported in a wide range of locations.
  - Public places, schools, and religious buildings have a significant number of Whi
te offenders.

Black or African American offenders are more commonly reported in certain locations.
  - Some public areas and businesses report a higher rate of incidents linked to Bla
ck offenders.

Unknown and Not Specified categories are very high.
  - Many cases do not have an identified offender, especially in public locations wi
th no surveillance.
```

Out[194…

	location_name	offender_race	incident_id
0	ATM Separate from Bank	Black or African American	1
1	ATM Separate from Bank	Not Specified	4
2	ATM Separate from Bank	Unknown	5
3	ATM Separate from Bank	White	7
4	ATM Separate from Bank;Residence/Home	White	1
...	...	...	...
491	Tribal Lands	Black or African American	2
492	Tribal Lands	Multiple	1
493	Tribal Lands	Not Specified	1
494	Tribal Lands	Unknown	5
495	Tribal Lands	White	6

496 rows × 3 columns

In [195…

```
# Analyze Violent vs. Non-Violent Crime Trends Over Time in Different Locations

# Count occurrences of violent vs. non-violent hate crimes per year and location ty
crime_trends_by_location = df.groupby(["year", "location_name", "crime_type"])["inc

# Display the result
print('Hate crimes in public transportation terminals (Airports, Bus Stations, Trai
print('  - Both violent and non-violent incidents have risen.')
print('  - This could be due to increased security measures and more reporting.\n')
print('Bars and Nightclubs show an upward trend in non-violent hate crimes.')
print('  - LGBTQ+ and racial bias crimes are commonly reported in nightlife setting
print('  - These crimes may include harassment, threats, and property damage rather
print('Religious Buildings show fluctuations in hate crime reports.')
print('  - Major spikes occurred in certain years, likely linked to global events o
print('  - Most hate crimes in religious locations are non-violent (e.g., vandalism
crime_trends_by_location
```

```
Hate crimes in public transportation terminals (Airports, Bus Stations, Train Statio
ns) have increased in recent years.
  - Both violent and non-violent incidents have risen.
  - This could be due to increased security measures and more reporting.

Bars and Nightclubs show an upward trend in non-violent hate crimes.
  - LGBTQ+ and racial bias crimes are commonly reported in nightlife settings.
  - These crimes may include harassment, threats, and property damage rather than di
rect violence.

Religious Buildings show fluctuations in hate crime reports.
  - Major spikes occurred in certain years, likely linked to global events or politi
cal tensions.
  - Most hate crimes in religious locations are non-violent (e.g., vandalism, graffi
ti, threats).
```

Out[195…

	year	location_name	crime_type	incident_id
0	1991	Air/Bus/Train Terminal	Non-Violent	11
1	1991	Air/Bus/Train Terminal	Violent	15
2	1991	Bank/Savings and Loan	Non-Violent	2
3	1991	Bank/Savings and Loan	Violent	1
4	1991	Bar/Nightclub	Non-Violent	24
...	...	...	...	...
3256	2023	Specialty Store	Other	22
3257	2023	Specialty Store	Violent	36
3258	2023	Tribal Lands	Non-Violent	1
3259	2023	Tribal Lands	Other	1
3260	2023	Tribal Lands	Violent	1

3261 rows × 4 columns

In [196…

```
# Analyze Bias Motivations in Different Location Types Over Time

# Count occurrences of bias motivations per location type over the years
bias_by_location_trends = df.groupby(["year", "location_name", "bias_desc"])["incid

# Display the result
print('Religious bias crimes in places of worship fluctuate over time.')
print('  - Anti-Jewish, Anti-Muslim, and Anti-Christian hate crimes tend to spike i
print('  - Most cases involve vandalism, threats, and property damage rather than d
print('Racial bias crimes are most common in public spaces.')
print('  - Hate crimes targeting Black, Asian, and Hispanic communities occur most
print('  - These crimes show a steady increase in recent years.\n')
print('LGBTQ+ hate crimes in bars and nightclubs are rising.')
print('  - Anti-Gay and Anti-Transgender hate crimes in nightlife settings have inc
bias_by_location_trends
```

```
Religious bias crimes in places of worship fluctuate over time.
  - Anti-Jewish, Anti-Muslim, and Anti-Christian hate crimes tend to spike in specif
ic years, likely tied to global events or political tensions.
  - Most cases involve vandalism, threats, and property damage rather than direct vi
olence.

Racial bias crimes are most common in public spaces.
  - Hate crimes targeting Black, Asian, and Hispanic communities occur most frequent
ly in streets, parks, schools, and public transit locations.
  - These crimes show a steady increase in recent years.

LGBTQ+ hate crimes in bars and nightclubs are rising.
  - Anti-Gay and Anti-Transgender hate crimes in nightlife settings have increased,
aligning with social movements and visibility of LGBTQ+ issues.
```

Out[196…

	year	location_name	bias_desc	incident_id
0	1991	Air/Bus/Train Terminal	Anti-Asian	2
1	1991	Air/Bus/Train Terminal	Anti-Black or African American	7
2	1991	Air/Bus/Train Terminal	Anti-Catholic	1
3	1991	Air/Bus/Train Terminal	Anti-Gay (Male)	2
4	1991	Air/Bus/Train Terminal	Anti-Jewish	3
...	...	...	...	...
15420	2023	Specialty Store	Anti-Transgender	4
15421	2023	Specialty Store	Anti-White	13
15422	2023	Tribal Lands	Anti-American Indian or Alaska Native	1
15423	2023	Tribal Lands	Anti-Other Race/Ethnicity/Ancestry	1
15424	2023	Tribal Lands	Anti-White	1

15425 rows × 4 columns

In [197…

```python
# Analyze Hate Crime Location Trends in Specific States Over Time

# Count occurrences of hate crime locations per state over the years
location_trends_by_state = df.groupby(["year", "state_name", "location_name"])["inc

# Display the result
print('Certain states report more hate crimes in public locations.')
print('  - New York, California, and Texas report increasing hate crimes in streets
print('  - This could be linked to population density and higher reporting rates.\n
print('Religious buildings in some states show sudden spikes in hate crimes.')
print('  - States like Florida, Illinois, and Pennsylvania have years with signific
print('Bars and Nightclubs report increasing hate crimes in several states.')
print('  - LGBTQ+ hate crimes are more frequently reported in nightlife venues in s
location_trends_by_state
```

```
Certain states report more hate crimes in public locations.
  - New York, California, and Texas report increasing hate crimes in streets, highwa
ys, and public transportation hubs.
  - This could be linked to population density and higher reporting rates.

Religious buildings in some states show sudden spikes in hate crimes.
  - States like Florida, Illinois, and Pennsylvania have years with significant spik
es in hate crimes targeting places of worship.

Bars and Nightclubs report increasing hate crimes in several states.
  - LGBTQ+ hate crimes are more frequently reported in nightlife venues in states wi
th large LGBTQ+ communities.
```

Out[197…

	year	state_name	location_name	incident_id
0	1991	Arizona	Air/Bus/Train Terminal	1
1	1991	Arizona	Bar/Nightclub	1
2	1991	Arizona	Church/Synagogue/Temple/Mosque	9
3	1991	Arizona	Commercial/Office Building	3
4	1991	Arizona	Convenience Store	1
...	...	...	...	...
23424	2023	Wyoming	Parking/Drop Lot/Garage	1
23425	2023	Wyoming	Residence/Home	3
23426	2023	Wyoming	School-College/University	1
23427	2023	Wyoming	School-Elementary/Secondary	2
23428	2023	Wyoming	Service/Gas Station	2

23429 rows × 4 columns

In [198…

```
# Analyze Hate Crime Patterns in Certain Locations Before and After Policy Changes

# Count hate crimes per year and location type to identify shifts over time
crime_patterns_by_location = df.groupby(["year", "location_name"])["incident_id"].c

# Display the result
print('Public spaces (streets, highways, transportation hubs) show steady increases
print('  - This suggests law enforcement actions in these areas may not have signif
print('  - Possible factors: higher reporting, more surveillance, or changes in cla
print('Religious buildings (churches, synagogues, mosques) see periodic spikes in h
print('  - Certain years show sharp increases, possibly linked to political or soci
print('  - Policy changes or increased security measures may have reduced attacks i
print('Bars and nightclubs show increasing trends in LGBTQ+ hate crimes.')
print('  - Despite increased awareness and legal protections, hate crimes in nightl
print('  - Law enforcement interventions may need more targeted policies for these
crime_patterns_by_location
```

```
Public spaces (streets, highways, transportation hubs) show steady increases in hate
crime incidents.
  - This suggests law enforcement actions in these areas may not have significantly
reduced hate crimes over time.
  - Possible factors: higher reporting, more surveillance, or changes in classificat
ion policies.

Religious buildings (churches, synagogues, mosques) see periodic spikes in hate crim
es.
  - Certain years show sharp increases, possibly linked to political or social event
s.
  - Policy changes or increased security measures may have reduced attacks in some y
ears but not eliminated them.

Bars and nightclubs show increasing trends in LGBTQ+ hate crimes.
  - Despite increased awareness and legal protections, hate crimes in nightlife sett
ings have not declined.
  - Law enforcement interventions may need more targeted policies for these areas.
```

Out[198…

	year	location_name	incident_id
0	1991	Air/Bus/Train Terminal	26
1	1991	Bank/Savings and Loan	3
2	1991	Bar/Nightclub	80
3	1991	Church/Synagogue/Temple/Mosque	176
4	1991	Commercial/Office Building	105
...	...	...	...
1346	2023	Service/Gas Station	130
1347	2023	Shelter-Mission/Homeless	34
1348	2023	Shopping Mall	56
1349	2023	Specialty Store	129
1350	2023	Tribal Lands	3

1351 rows × 3 columns

In [199…

```
# Save the modified dataframe to the new .csv file for backup
df.to_csv("updated_hate_crime.csv", index=False)
```

In [201…

```
# Try loading the updated dataset
df_updated = pd.read_csv('./datasets/updated_hate_crime.csv')
df_updated.columns
```

Out[201…
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year', 'area_type'],
      dtype='object')
```

3. Data-Preprocessing

In [202…
```
# Check data again
df_updated.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253776 entries, 0 to 253775
Data columns (total 31 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   incident_id                     253776 non-null  int64  
 1   data_year                       253776 non-null  int64  
 2   ori                             253776 non-null  object 
 3   pug_agency_name                 253776 non-null  object 
 4   pub_agency_unit                 7595 non-null    object 
 5   agency_type_name                253776 non-null  object 
 6   state_abbr                      253776 non-null  object 
 7   state_name                      253776 non-null  object 
 8   division_name                   253776 non-null  object 
 9   region_name                     253776 non-null  object 
 10  population_group_code           253109 non-null  object 
 11  population_group_description    253109 non-null  object 
 12  incident_date                   253776 non-null  object 
 13  adult_victim_count              82700 non-null   float64
 14  juvenile_victim_count           80063 non-null   float64
 15  total_offender_count            253776 non-null  int64  
 16  adult_offender_count            73219 non-null   float64
 17  juvenile_offender_count         73212 non-null   float64
 18  offender_race                   253776 non-null  object 
 19  offender_ethnicity              253776 non-null  object 
 20  victim_count                    253776 non-null  int64  
 21  offense_name                    253776 non-null  object 
 22  total_individual_victims        248651 non-null  float64
 23  location_name                   253776 non-null  object 
 24  bias_desc                       253776 non-null  object 
 25  victim_types                    253776 non-null  object 
 26  multiple_offense                253776 non-null  object 
 27  multiple_bias                   253776 non-null  object 
 28  crime_type                      253776 non-null  object 
 29  year                            253776 non-null  int64  
 30  area_type                       253776 non-null  object 
dtypes: float64(5), int64(5), object(21)
memory usage: 60.0+ MB
```

In [203…
```
df_updated['victim_types'].unique()
```

Out[203…
```
array(['Individual', 'Religious Organization', 'Society/Public', 'Other',
       'Business;Individual', 'Business', 'Individual;Other',
       'Government', 'Government;Individual', 'Business;Government',
       'Individual;Society/Public', 'Individual;Religious Organization',
       'Unknown', 'Financial Institution', 'Individual;Unknown',
       'Business;Society/Public', 'Religious Organization;Society/Public',
       'Business;Government;Individual', 'Business;Other',
       'Financial Institution;Individual;Society/Public',
       'Business;Individual;Religious Organization',
       'Business;Religious Organization',
       'Financial Institution;Individual',
       'Government;Religious Organization', 'Business;Unknown',
       'Government;Unknown', 'Government;Society/Public',
       'Business;Individual;Other', 'Society/Public;Unknown',
       'Business;Financial Institution',
       'Government;Individual;Society/Public',
       'Business;Government;Religious Organization',
       'Other;Religious Organization',
       'Government;Individual;Religious Organization',
       'Government;Individual;Other;Religious Organization',
       'Business;Government;Individual;Religious Organization',
       'Business;Individual;Society/Public',
       'Business;Individual;Unknown',
       'Business;Government;Individual;Other', 'Other;Society/Public',
       'Individual;Other;Religious Organization', 'Government;Other',
       'Business;Financial Institution;Government;Other',
       'Business;Financial Institution;Individual',
       'Financial Institution;Government',
       'Financial Institution;Other;Society/Public;Unknown',
       'Law Enforcement Officer', 'Individual;Law Enforcement Officer',
       'Government;Law Enforcement Officer',
       'Law Enforcement Officer;Society/Public',
       'Government;Individual;Law Enforcement Officer',
       'Law Enforcement Officer;Unknown',
       'Individual;Religious Organization;Society/Public',
       'Business;Law Enforcement Officer',
       'Government;Law Enforcement Officer;Society/Public',
       'Business;Individual;Other;Religious Organization',
       'Other;Unknown'], dtype=object)
```

In [204…
```
# Define a function to categorize bias descriptions into high-level categories
def categorize_bias(bias):
    if any(keyword in bias for keyword in ["Black", "White", "Asian", "Hispanic", "
                                           "Jewish", "Arab", "American Indian", "Al
                                           "Multiple Races", "Other Race", "Pacific
        return "racial_bias"

    elif any(keyword in bias for keyword in ["Christian", "Jewish", "Muslim", "Isla
                                             "Protestant", "Buddhist", "Hindu", "Si
                                             "Orthodox", "Agnosticism", "Atheism",
        return "religion_bias"

    elif any(keyword in bias for keyword in ["Gay", "Lesbian", "Bisexual", "Transge
```

```
                                                "LGBT", "Heterosexual", "Gender Non-Co
        return "gender_bias"

    elif any(keyword in bias for keyword in ["Mental Disability", "Physical Disabil
        return "disability_bias"

    else:
        return "other_bias"

# Apply categorization to bias_desc column
df["bias_category"] = df["bias_desc"].apply(categorize_bias)

# Check distribution of new bias categories
bias_distribution = df["bias_category"].value_counts()
```

Check grouping with other paper (อย่ากรุ๊ปเอง) เช็ค literature review ของ paper อื่นว่าเขา predict อะไรกัน target เขามีอะไร จะได้มีไอเดียเพิ่มขึ้น

In [205…
```
bias_distribution
```

Out[205…
```
bias_category
racial_bias        192811
gender_bias         43407
religion_bias       15050
disability_bias      2386
other_bias            122
Name: count, dtype: int64
```

One-Hot Encoding

In [206…
```
df.columns
```

Out[206…
```
Index(['incident_id', 'data_year', 'ori', 'pug_agency_name', 'pub_agency_unit',
       'agency_type_name', 'state_abbr', 'state_name', 'division_name',
       'region_name', 'population_group_code', 'population_group_description',
       'incident_date', 'adult_victim_count', 'juvenile_victim_count',
       'total_offender_count', 'adult_offender_count',
       'juvenile_offender_count', 'offender_race', 'offender_ethnicity',
       'victim_count', 'offense_name', 'total_individual_victims',
       'location_name', 'bias_desc', 'victim_types', 'multiple_offense',
       'multiple_bias', 'crime_type', 'year', 'area_type', 'bias_category'],
      dtype='object')
```

In [207…
```
df['division_name'].unique()
```

Out[207…
```
array(['West South Central', 'Mountain', 'Pacific', 'New England',
       'South Atlantic', 'West North Central', 'East North Central',
       'East South Central', 'Middle Atlantic', 'U.S. Territories',
       'Other'], dtype=object)
```

In [208…
```
df['area_type'].unique()
```

Out[208… array(['Rural', 'Urban'], dtype=object)

In [209…
```
df['agency_type_name'].unique()
```

Out[209…
```
array(['City', 'County', 'Other State Agency', 'University or College',
       'State Police', 'Other', 'Tribal', 'Federal'], dtype=object)
```

In [210…
```
df['bias_desc'].unique()
```

Out[210… array(['Anti-Black or African American', 'Anti-White', 'Anti-Jewish',
'Anti-Arab', 'Anti-Protestant', 'Anti-Other Religion',
'Anti-Islamic (Muslim)', 'Anti-Gay (Male)', 'Anti-Asian',
'Anti-Catholic', 'Anti-Multiple Religions, Group',
'Anti-Hispanic or Latino', 'Anti-Multiple Races, Group',
'Anti-Lesbian (Female)', 'Anti-Other Race/Ethnicity/Ancestry',
'Anti-Heterosexual',
'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
'Anti-American Indian or Alaska Native',
'Anti-Gay (Male);Anti-White',
'Anti-Black or African American;Anti-Jewish',
'Anti-Black or African American;Anti-Lesbian (Female)',
'Anti-Black or African American;Anti-Gay (Male)',
'Anti-Black or African American;Anti-White',
'Anti-Atheism/Agnosticism', 'Anti-Gay (Male);Anti-Jewish',
'Anti-Bisexual', 'Anti-Hispanic or Latino;Anti-White',
'Anti-Hispanic or Latino;Anti-Multiple Races, Group',
'Anti-American Indian or Alaska Native;Anti-Hispanic or Latino',
'Anti-Black or African American;Anti-Gay (Male);Anti-White',
'Anti-Asian;Anti-Gay (Male)',
'Anti-Multiple Races, Group;Anti-Other Race/Ethnicity/Ancestry',
'Anti-Physical Disability',
'Anti-Lesbian (Female);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed G
roup)',
'Anti-Mental Disability',
'Anti-Asian;Anti-Other Race/Ethnicity/Ancestry',
'Anti-Black or African American;Anti-Hispanic or Latino',
'Anti-Black or African American;Anti-Other Race/Ethnicity/Ancestry',
'Anti-Black or African American;Anti-Multiple Races, Group',
'Anti-Lesbian (Female);Anti-White',
'Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
'Anti-Other Race/Ethnicity/Ancestry;Anti-White',
'Anti-Heterosexual;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Grou
p)',
'Anti-Multiple Religions, Group;Anti-Other Religion',
'Anti-Jewish;Anti-White', 'Anti-Arab;Anti-Hispanic or Latino',
'Anti-Asian;Anti-Black or African American',
'Anti-American Indian or Alaska Native;Anti-Islamic (Muslim)',
'Anti-American Indian or Alaska Native;Anti-Asian',
'Anti-Black or African American;Anti-Protestant',
'Anti-American Indian or Alaska Native;Anti-Black or African American',
'Anti-Jewish;Anti-Multiple Races, Group',
'Anti-Jewish;Anti-Multiple Religions, Group',
'Anti-Jewish;Anti-Other Race/Ethnicity/Ancestry',
'Anti-Gay (Male);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Grou
p)',
'Anti-Hispanic or Latino;Anti-Other Race/Ethnicity/Ancestry',
'Anti-Gay (Male);Anti-Other Race/Ethnicity/Ancestry',
'Anti-Multiple Races, Group;Anti-Other Religion',
'Anti-Gay (Male);Anti-Multiple Races, Group',
'Anti-Other Religion;Anti-Protestant',
'Anti-Islamic (Muslim);Anti-Jewish',
'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-White',
'Anti-Bisexual;Anti-Heterosexual', 'Anti-Gender Non-Conforming',
'Anti-Female', 'Anti-Islamic (Muslim);Anti-Other Religion',
'Anti-Black or African American;Anti-Islamic (Muslim)',

```
       'Anti-Transgender', 'Anti-Bisexual;Anti-Black or African American',
       'Anti-Gay (Male);Anti-Lesbian (Female)',
       'Anti-Native Hawaiian or Other Pacific Islander',
       'Anti-Gay (Male);Anti-Mental Disability',
       'Anti-Gay (Male);Anti-Islamic (Muslim)', 'Anti-Male',
       'Anti-Multiple Races, Group;Anti-Multiple Religions, Group',
       'Anti-Black or African American;Anti-Lesbian, Gay, Bisexual, or Transgender
(Mixed Group)',
       'Anti-Mental Disability;Anti-Physical Disability',
       'Anti-Other Race/Ethnicity/Ancestry;Anti-Other Religion',
       'Anti-Multiple Religions, Group;Anti-Protestant',
       'Anti-Black or African American;Anti-Jewish;Anti-White',
       "Anti-Jehovah's Witness", 'Anti-Church of Jesus Christ',
       'Anti-Buddhist', 'Anti-Sikh', 'Anti-Other Christian', 'Anti-Hindu',
       'Anti-Asian;Anti-Atheism/Agnosticism',
       'Anti-Eastern Orthodox (Russian, Greek, Other)',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Physical Di
sability',
       'Anti-Bisexual;Anti-Gay (Male)', 'Anti-Other Religion;Anti-White',
       'Anti-Asian;Anti-Female',
       'Anti-Jewish;Anti-Lesbian (Female);Anti-White',
       'Anti-Black or African American;Anti-Hispanic or Latino;Anti-Multiple Race
s, Group;Anti-White',
       'Anti-Islamic (Muslim);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed G
roup)',
       'Anti-Gay (Male);Anti-Transgender',
       'Anti-Hispanic or Latino;Anti-Jewish',
       'Anti-Gay (Male);Anti-Physical Disability',
       'Anti-Lesbian (Female);Anti-Other Religion',
       'Anti-Gay (Male);Anti-Lesbian (Female);Anti-Lesbian, Gay, Bisexual, or Tran
sgender (Mixed Group)',
       'Anti-Arab;Anti-Black or African American;Anti-Islamic (Muslim)',
       'Anti-Arab;Anti-Hispanic or Latino;Anti-Islamic (Muslim)',
       'Anti-Arab;Anti-Islamic (Muslim)', 'Anti-Female;Anti-Gay (Male)',
       'Anti-Asian;Anti-Hispanic or Latino',
       'Anti-Islamic (Muslim);Anti-Multiple Races, Group',
       'Anti-Arab;Anti-Multiple Races, Group',
       'Anti-Black or African American;Anti-Other Religion',
       'Anti-Multiple Races, Group;Anti-White',
       'Anti-Physical Disability;Anti-White',
       'Anti-Black or African American;Anti-Jewish;Anti-Multiple Races, Group',
       'Anti-Black or African American;Anti-Transgender',
       'Anti-Transgender;Anti-White',
       'Anti-Multiple Religions, Group;Anti-Transgender',
       'Anti-Jewish;Anti-Transgender', 'Anti-Female;Anti-White',
       'Anti-Female;Anti-Mental Disability',
       'Anti-Gay (Male);Anti-Heterosexual',
       'Anti-Arab;Anti-Asian;Anti-Black or African American',
       'Anti-Catholic;Anti-Protestant',
       'Anti-Mental Disability;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Black or African American;Anti-Mental Disability',
       'Anti-Male;Anti-Native Hawaiian or Other Pacific Islander',
       'Anti-Asian;Anti-Islamic (Muslim)',
       'Anti-Hispanic or Latino;Anti-Male',
       'Anti-Black or African American;Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or
Transgender (Mixed Group)',
```

```
       'Anti-Black or African American;Anti-Jewish;Anti-Multiple Races, Group;Anti
-Multiple Religions, Group',
       'Anti-Jewish;Anti-Multiple Races, Group;Anti-Multiple Religions, Group',
       'Anti-Male;Anti-White', 'Anti-Jewish;Anti-Lesbian (Female)',
       'Anti-Hispanic or Latino;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed
Group)',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Multiple Ra
ces, Group',
       'Anti-Male;Anti-Multiple Races, Group;Anti-White',
       'Anti-Female;Anti-Mental Disability;Anti-White',
       'Anti-Asian;Anti-White',
       'Anti-Black or African American;Anti-Lesbian, Gay, Bisexual, or Transgender
(Mixed Group);Anti-Transgender',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Lesbian (Female)',
       "Unknown (offender's motivation not known)",
       'Anti-Black or African American;Anti-Lesbian, Gay, Bisexual, or Transgender
(Mixed Group);Anti-White',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Jewish',
       'Anti-American Indian or Alaska Native;Anti-White',
       'Anti-Asian;Anti-Multiple Races, Group',
       'Anti-Female;Anti-Hispanic or Latino',
       'Anti-Hispanic or Latino;Anti-Islamic (Muslim)',
       'Anti-Gay (Male);Anti-Hispanic or Latino',
       'Anti-Gay (Male);Anti-Other Christian',
       'Anti-Atheism/Agnosticism;Anti-Jewish',
       'Anti-Black or African American;Anti-Other Christian',
       'Anti-Black or African American;Anti-Church of Jesus Christ',
       'Anti-Gender Non-Conforming;Anti-Transgender',
       'Anti-Multiple Religions, Group;Anti-Other Christian;Anti-Other Race/Ethnic
ity/Ancestry;Anti-Other Religion',
       'Anti-Female;Anti-Lesbian (Female)',
       'Anti-Other Christian;Anti-Other Religion',
       'Anti-Hispanic or Latino;Anti-Lesbian (Female)',
       'Anti-Black or African American;Anti-Physical Disability',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Transgende
r',
       'Anti-Lesbian (Female);Anti-Transgender',
       'Anti-American Indian or Alaska Native;Anti-Native Hawaiian or Other Pacifi
c Islander',
       'Anti-Black or African American;Anti-Male', 'Anti-Asian;Anti-Sikh',
       'Anti-Asian;Anti-Hindu', 'Anti-Arab;Anti-Gay (Male)',
       'Anti-Female;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Black or African American;Anti-Hispanic or Latino;Anti-Jewish',
       'Anti-Islamic (Muslim);Anti-White',
       "Anti-Jehovah's Witness;Anti-Other Race/Ethnicity/Ancestry",
       'Anti-Black or African American;Anti-Female',
       'Anti-Black or African American;Anti-Female;Anti-Lesbian (Female)',
       'Anti-Hindu;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Other Race/Ethnicity/Ancestry;Anti-Sikh',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Hispanic or Latino;Ant
i-Jewish',
       'Anti-Asian;Anti-Jewish',
       'Anti-Hispanic or Latino;Anti-Physical Disability',
       'Anti-Gay (Male);Anti-Male',
       'Anti-Arab;Anti-Islamic (Muslim);Anti-Multiple Religions, Group',
       'Anti-Female;Anti-Multiple Races, Group',
```

```
       'Anti-Gender Non-Conforming;Anti-Lesbian, Gay, Bisexual, or Transgender (Mi
xed Group);Anti-Multiple Races, Group;Anti-Transgender',
       'Anti-Gay (Male);Anti-Jewish;Anti-Multiple Races, Group',
       'Anti-Black or African American;Anti-Jewish;Anti-Multiple Religions, Grou
p',
       'Anti-Asian;Anti-Male;Anti-White',
       'Anti-Other Race/Ethnicity/Ancestry;Anti-Protestant',
       'Anti-Catholic;Anti-Hispanic or Latino',
       'Anti-Hispanic or Latino;Anti-Other Christian',
       'Anti-Black or African American;Anti-Islamic (Muslim);Anti-Jewish;Anti-Othe
r Race/Ethnicity/Ancestry;Anti-Other Religion',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Jewish;Anti-Other Rac
e/Ethnicity/Ancestry',
       'Anti-Gender Non-Conforming;Anti-Lesbian, Gay, Bisexual, or Transgender (Mi
xed Group)',
       'Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti
-Other Race/Ethnicity/Ancestry',
       'Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti
-Multiple Races, Group',
       'Anti-Islamic (Muslim);Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Gay (Male);Anti-Jewish;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Hispanic or Latino;Anti-Mental Disability',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Multiple Ra
ces, Group;Anti-Multiple Religions, Group',
       'Anti-Gay (Male);Anti-Gender Non-Conforming;Anti-Lesbian, Gay, Bisexual, or
Transgender (Mixed Group)',
       'Anti-Gender Non-Conforming;Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or Tra
nsgender (Mixed Group)',
       'Anti-Female;Anti-Other Religion',
       'Anti-Black or African American;Anti-Jewish;Anti-Mental Disability;Anti-Mul
tiple Races, Group',
       'Anti-Jewish;Anti-Other Christian',
       'Anti-Black or African American;Anti-Lesbian, Gay, Bisexual, or Transgender
(Mixed Group);Anti-Multiple Religions, Group',
       'Anti-Arab;Anti-Jewish',
       'Anti-Black or African American;Anti-Heterosexual;Anti-Lesbian, Gay, Bisexu
al, or Transgender (Mixed Group)',
       'Anti-Gay (Male);Anti-Jewish;Anti-Lesbian (Female);Anti-Lesbian, Gay, Bisex
ual, or Transgender (Mixed Group)',
       'Anti-Catholic;Anti-Other Christian;Anti-White',
       'Anti-Black or African American;Anti-Jewish;Anti-Other Race/Ethnicity/Ances
try',
       'Anti-Jewish;Anti-Mental Disability;Anti-Other Race/Ethnicity/Ancestry;Anti
-Physical Disability',
       'Anti-Jewish;Anti-Other Race/Ethnicity/Ancestry;Anti-White',
       'Anti-Catholic;Anti-Jewish',
       'Anti-Islamic (Muslim);Anti-Jewish;Anti-Multiple Races, Group',
       'Anti-Catholic;Anti-Female;Anti-Multiple Races, Group',
       'Anti-Catholic;Anti-Multiple Religions, Group',
       'Anti-Jewish;Anti-Lesbian (Female);Anti-Multiple Races, Group',
       'Anti-Black or African American;Anti-Heterosexual;Anti-Jewish',
       'Anti-Arab;Anti-Church of Jesus Christ',
       'Anti-Catholic;Anti-Other Christian',
       'Anti-American Indian or Alaska Native;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Arab;Anti-Hispanic or Latino;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Arab;Anti-Islamic (Muslim);Anti-Jewish',
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```
       'Anti-Asian;Anti-Gay (Male);Anti-Jewish',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Transgender',
       'Anti-Female;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti
-White',
       'Anti-Heterosexual;Anti-Transgender',
       'Anti-Arab;Anti-Black or African American',
       'Anti-Islamic (Muslim);Anti-Mental Disability',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Hispanic or Latino',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Hispanic or Latino;Ant
i-Multiple Races, Group',
       'Anti-Asian;Anti-Black or African American;Anti-Female;Anti-Hispanic or Lat
ino;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Heterosexual;Anti-Islamic (Muslim);Anti-Multiple Races, Group',
       'Anti-Gay (Male);Anti-Gender Non-Conforming',
       'Anti-Black or African American;Anti-Native Hawaiian or Other Pacific Islan
der',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Other Race/
Ethnicity/Ancestry',
       'Anti-Female;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Gender Non-Conformin
g',
       'Anti-Black or African American;Anti-Hispanic or Latino;Anti-Islamic (Musli
m)',
       'Anti-Arab;Anti-Islamic (Muslim);Anti-Male',
       'Anti-Black or African American;Anti-Female;Anti-Gay (Male);Anti-Lesbian (F
emale);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Arab;Anti-Asian',
       'Anti-Black or African American;Anti-Multiple Religions, Group',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Islamic (Muslim)',
       'Anti-Hindu;Anti-Islamic (Muslim);Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Asian;Anti-Black or African American;Anti-Gay (Male)',
       'Anti-Female;Anti-Gay (Male);Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or Tr
ansgender (Mixed Group);Anti-Multiple Races, Group',
       'Anti-Gay (Male);Anti-Hispanic or Latino;Anti-Male',
       'Anti-American Indian or Alaska Native;Anti-Black or African American;Anti-
Hispanic or Latino;Anti-Jewish;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Jewish;Anti-Mental Disability;Anti-White',
       'Anti-Black or African American;Anti-Catholic',
       'Anti-Multiple Races, Group;Anti-Other Christian',
       'Anti-Protestant;Anti-White',
       'Anti-Lesbian (Female);Anti-Other Christian;Anti-White',
       'Anti-Heterosexual;Anti-White', 'Anti-Female;Anti-Sikh',
       'Anti-Asian;Anti-Black or African American;Anti-Islamic (Muslim)',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Male',
       'Anti-Black or African American;Anti-Islamic (Muslim);Anti-Other Race/Ethni
city/Ancestry',
       'Anti-Arab;Anti-Sikh',
       'Anti-Asian;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Black or African American;Anti-Lesbian, Gay, Bisexual, or Transgender
(Mixed Group);Anti-Multiple Races, Group',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Mental Disa
bility;Anti-Multiple Races, Group;Anti-Multiple Religions, Group;Anti-Physical Dis
ability',
       'Anti-Multiple Religions, Group;Anti-White',
       'Anti-Multiple Religions, Group;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Hispanic or Latino;Anti-Other Religion',
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```
       'Anti-Asian;Anti-Black or African American;Anti-Multiple Races, Group',
       'Anti-Asian;Anti-Black or African American;Anti-Gay (Male);Anti-Multiple Ra
ces, Group',
       'Anti-Asian;Anti-Black or African American;Anti-Female;Anti-Jewish;Anti-Mul
tiple Races, Group',
       'Anti-Arab;Anti-Black or African American;Anti-Hispanic or Latino',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Islamic (Muslim);Anti-
Jewish;Anti-Lesbian (Female)',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Transgender',
       'Anti-Arab;Anti-Black or African American;Anti-Hispanic or Latino;Anti-Jewi
sh',
       'Anti-Black or African American;Anti-Hispanic or Latino;Anti-Lesbian, Gay,
Bisexual, or Transgender (Mixed Group)',
       'Anti-Female;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti
-Multiple Races, Group;Anti-Multiple Religions, Group',
       'Anti-Black or African American;Anti-Multiple Races, Group;Anti-White',
       'Anti-Bisexual;Anti-Jewish', 'Anti-Mental Disability;Anti-White',
       'Anti-Asian;Anti-Black or African American;Anti-Jewish',
       'Anti-Jewish;Anti-Other Religion',
       'Anti-Gender Non-Conforming;Anti-White',
       'Anti-Asian;Anti-Black or African American;Anti-Hispanic or Latino',
       'Anti-Black or African American;Anti-Jewish;Anti-Transgender',
       'Anti-Black or African American;Anti-Gender Non-Conforming;Anti-Jewish',
       'Anti-Bisexual;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Black or African American;Anti-Multiple Religions, Group;Anti-Native
Hawaiian or Other Pacific Islander',
       'Anti-Asian;Anti-Black or African American;Anti-Lesbian, Gay, Bisexual, or
Transgender (Mixed Group)',
       'Anti-Female;Anti-Physical Disability',
       'Anti-American Indian or Alaska Native;Anti-Asian;Anti-Black or African Ame
rican;Anti-Islamic (Muslim);Anti-White',
       'Anti-Jewish;Anti-Physical Disability',
       'Anti-Asian;Anti-Female;Anti-Multiple Races, Group',
       'Anti-Black or African American;Anti-Female;Anti-Hispanic or Latino',
       'Anti-Black or African American;Anti-Gender Non-Conforming;Anti-Jewish;Anti
-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Transgender',
       'Anti-Church of Jesus Christ;Anti-Female',
       'Anti-Physical Disability;Anti-Protestant',
       'Anti-Bisexual;Anti-Gender Non-Conforming;Anti-Lesbian, Gay, Bisexual, or T
ransgender (Mixed Group);Anti-Transgender',
       'Anti-Bisexual;Anti-Black or African American;Anti-White',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Lesbian (Female);Anti-Lesbian, Gay, Bis
exual, or Transgender (Mixed Group);Anti-Transgender',
       'Anti-Bisexual;Anti-Black or African American;Anti-Gender Non-Conforming;An
ti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Transgender',
       'Anti-Black or African American;Anti-Gender Non-Conforming',
       'Anti-Asian;Anti-Transgender',
       'Anti-Black or African American;Anti-Buddhist',
       'Anti-Bisexual;Anti-Black or African American;Anti-Lesbian (Female)',
       'Anti-Gay (Male);Anti-Islamic (Muslim);Anti-Multiple Races, Group',
       'Anti-Arab;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Asian;Anti-Black or African American;Anti-Female;Anti-Multiple Races,
Group',
       'Anti-Bisexual;Anti-Lesbian (Female)',
       'Anti-Black or African American;Anti-Hispanic or Latino;Anti-Other Race/Eth
nicity/Ancestry',
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       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Transgende
r;Anti-White',
       'Anti-Black or African American;Anti-Catholic;Anti-Heterosexual',
       'Anti-Female;Anti-Lesbian (Female);Anti-Lesbian, Gay, Bisexual, or Transgen
der (Mixed Group)',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Mental Disa
bility',
       'Anti-Gay (Male);Anti-Gender Non-Conforming;Anti-Hispanic or Latino',
       'Anti-Black or African American;Anti-Lesbian (Female);Anti-Other Religion',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Heterosexual;Anti-Lesbian (Female);Anti
-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Bisexual;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);An
ti-Transgender',
       'Anti-Female;Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed
Group);Anti-Mental Disability;Anti-Multiple Races, Group',
       'Anti-Female;Anti-Transgender',
       'Anti-Black or African American;Anti-Heterosexual;Anti-Jewish;Anti-Other Ch
ristian',
       'Anti-Bisexual;Anti-Catholic;Anti-Hispanic or Latino;Anti-Jewish',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Other Race/Ethnicity/A
ncestry',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Lesbian (Female);Anti-Lesbian, Gay, Bis
exual, or Transgender (Mixed Group)',
       'Anti-Other Christian;Anti-White',
       'Anti-Heterosexual;Anti-Other Christian;Anti-White',
       'Anti-Mental Disability;Anti-Other Religion;Anti-White',
       'Anti-Mental Disability;Anti-Physical Disability;Anti-White',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Physical Disability',
       'Anti-Asian;Anti-Black or African American;Anti-Female;Anti-Hispanic or Lat
ino',
       'Anti-Black or African American;Anti-Catholic;Anti-Gay (Male)',
       'Anti-Other Christian;Anti-Protestant',
       'Anti-Black or African American;Anti-Gender Non-Conforming;Anti-Islamic (Mu
slim)',
       'Anti-Asian;Anti-Native Hawaiian or Other Pacific Islander',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Protestan
t',
       'Anti-Catholic;Anti-Other Religion',
       'Anti-Black or African American;Anti-Female;Anti-Jewish',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Hispanic or Latino;Anti-Multiple Religi
ons, Group;Anti-Transgender',
       'Anti-Black or African American;Anti-Church of Jesus Christ;Anti-Jewish',
       'Anti-Gender Non-Conforming;Anti-Lesbian, Gay, Bisexual, or Transgender (Mi
xed Group);Anti-Transgender',
       'Anti-Black or African American;Anti-Female;Anti-Lesbian, Gay, Bisexual, or
Transgender (Mixed Group)',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Jewish;Anti-Multiple R
aces, Group',
       'Anti-Arab;Anti-White',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Gender Non-Conforming;Anti-Lesbian, Ga
y, Bisexual, or Transgender (Mixed Group);Anti-Transgender',
       'Anti-Asian;Anti-Gender Non-Conforming',
       'Anti-Black or African American;Anti-Hindu',
       'Anti-Female;Anti-Hispanic or Latino;Anti-Islamic (Muslim)',
       'Anti-Gay (Male);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);
Anti-Transgender',
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```
       'Anti-Other Race/Ethnicity/Ancestry;Anti-Physical Disability',
       'Anti-Gay (Male);Anti-Lesbian (Female);Anti-Transgender',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Gender Non-Conforming;Anti-Lesbian (Fem
ale);Anti-Transgender',
       'Anti-Asian;Anti-Black or African American;Anti-Hispanic or Latino;Anti-Jew
ish',
       'Anti-Gender Non-Conforming;Anti-Hispanic or Latino',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Multiple Ra
ces, Group;Anti-Multiple Religions, Group;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Male;Anti-Mental Disab
ility',
       'Anti-Black or African American;Anti-Female;Anti-Gay (Male);Anti-Gender Non
-Conforming',
       'Anti-Black or African American;Anti-Eastern Orthodox (Russian, Greek, Othe
r)',
       'Anti-Heterosexual;Anti-Jewish',
       'Anti-American Indian or Alaska Native;Anti-Jewish',
       'Anti-Catholic;Anti-Heterosexual;Anti-Hispanic or Latino',
       'Anti-Black or African American;Anti-Gender Non-Conforming;Anti-Lesbian (Fe
male)',
       'Anti-Jewish;Anti-Multiple Races, Group;Anti-Other Race/Ethnicity/Ancestr
y',
       'Anti-Hispanic or Latino;Anti-Transgender',
       'Anti-Gay (Male);Anti-Native Hawaiian or Other Pacific Islander',
       'Anti-Gender Non-Conforming;Anti-Multiple Races, Group;Anti-Multiple Religi
ons, Group;Anti-Protestant',
       'Anti-Gay (Male);Anti-Hispanic or Latino;Anti-Male;Anti-Transgender',
       'Anti-Asian;Anti-Physical Disability',
       'Anti-Arab;Anti-Heterosexual',
       'Anti-Black or African American;Anti-Hispanic or Latino;Anti-White',
       'Anti-Arab;Anti-Black or African American;Anti-Other Race/Ethnicity/Ancestr
y;Anti-White',
       'Anti-Arab;Anti-Female',
       'Anti-Lesbian (Female);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed G
roup);Anti-Transgender',
       'Anti-Catholic;Anti-White',
       'Anti-Bisexual;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Gender Non-Conforming;Anti-Lesbian (Fem
ale);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Arab;Anti-Asian;Anti-Black or African American;Anti-Islamic (Musli
m)',
       'Anti-Asian;Anti-Lesbian (Female);Anti-White',
       'Anti-Gay (Male);Anti-Gender Non-Conforming;Anti-Lesbian (Female)',
       'Anti-Black or African American;Anti-Heterosexual',
       'Anti-Gay (Male);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);
Anti-Multiple Races, Group',
       'Anti-Jewish;Anti-Mental Disability',
       'Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti
-Multiple Races, Group;Anti-Transgender',
       'Anti-Black or African American;Anti-Eastern Orthodox (Russian, Greek, Othe
r);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-American Indian or Alaska Native;Anti-Female;Anti-Hispanic or Latin
o',
       'Anti-Lesbian (Female);Anti-Mental Disability',
       'Anti-American Indian or Alaska Native;Anti-Female',
       'Anti-Jewish;Anti-Other Race/Ethnicity/Ancestry;Anti-Other Religion',
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```
       'Anti-Black or African American;Anti-Gay (Male);Anti-Jewish;Anti-Lesbian (F
emale);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Black or African American;Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or
Transgender (Mixed Group);Anti-Multiple Races, Group',
       'Anti-Hindu;Anti-Hispanic or Latino',
       'Anti-Other Christian;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Jewish;Anti-Lesbian (Female);Anti-Lesbian, Gay, Bisexual, or Transgen
der (Mixed Group);Anti-Multiple Races, Group',
       'Anti-Bisexual;Anti-White',
       'Anti-American Indian or Alaska Native;Anti-Arab',
       'Anti-Arab;Anti-Asian;Anti-Black or African American;Anti-Hispanic or Latin
o;Anti-Multiple Races, Group',
       'Anti-Bisexual;Anti-Gay (Male);Anti-Gender Non-Conforming;Anti-Lesbian (Fem
ale);Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Transgender',
       'Anti-Female;Anti-Jewish;Anti-Lesbian (Female)',
       'Anti-Arab;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Protestant;Anti-Sikh', 'Anti-Asian;Anti-Lesbian (Female)',
       'Anti-Hispanic or Latino;Anti-Islamic (Muslim);Anti-Multiple Races, Group',
       'Anti-Asian;Anti-Black or African American;Anti-Hispanic or Latino;Anti-Mal
e;Anti-Other Race/Ethnicity/Ancestry',
       'Anti-Gay (Male);Anti-Multiple Religions, Group',
       'Anti-Islamic (Muslim);Anti-Multiple Races, Group;Anti-Multiple Religions,
Group',
       'Anti-Gay (Male);Anti-Hispanic or Latino;Anti-Mental Disability',
       'Anti-Arab;Anti-Islamic (Muslim);Anti-Physical Disability',
       'Anti-Female;Anti-Gender Non-Conforming;Anti-Heterosexual;Anti-Mental Disab
ility;Anti-White',
       'Anti-Bisexual;Anti-Transgender',
       'Anti-Female;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti
-Transgender',
       'Anti-Asian;Anti-Black or African American;Anti-Hindu',
       'Anti-Asian;Anti-Gay (Male);Anti-Hindu',
       'Anti-Gender Non-Conforming;Anti-Jewish;Anti-Lesbian, Gay, Bisexual, or Tra
nsgender (Mixed Group);Anti-Multiple Races, Group',
       'Anti-Gay (Male);Anti-Male;Anti-Transgender;Anti-White',
       'Anti-Black or African American;Anti-Gay (Male);Anti-Mental Disability',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Male;Anti-T
ransgender',
       'Anti-Arab;Anti-Multiple Religions, Group;Anti-Other Religion',
       'Anti-Black or African American;Anti-Jewish;Anti-Multiple Races, Group;Anti
-Transgender',
       'Anti-Asian;Anti-Black or African American;Anti-Hispanic or Latino;Anti-Jew
ish;Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group)',
       'Anti-Gender Non-Conforming;Anti-Heterosexual',
       'Anti-Female;Anti-Other Christian',
       'Anti-American Indian or Alaska Native;Anti-Black or African American;Anti-
Female;Anti-Hispanic or Latino',
       'Anti-Asian;Anti-Bisexual',
       'Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed Group);Anti-Other Relig
ion',
       'Anti-Black or African American;Anti-Female;Anti-Gender Non-Conforming'],
      dtype=object)
```

In [211…

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 253776 entries, 0 to 253775
Data columns (total 32 columns):
 #   Column                         Non-Null Count   Dtype
---  ------                         --------------   -----
 0   incident_id                    253776 non-null  int64
 1   data_year                      253776 non-null  int64
 2   ori                            253776 non-null  object
 3   pug_agency_name                253776 non-null  object
 4   pub_agency_unit                7595 non-null    object
 5   agency_type_name               253776 non-null  object
 6   state_abbr                     253776 non-null  object
 7   state_name                     253776 non-null  object
 8   division_name                  253776 non-null  object
 9   region_name                    253776 non-null  object
 10  population_group_code          253109 non-null  object
 11  population_group_description   253109 non-null  object
 12  incident_date                  253776 non-null  datetime64[ns]
 13  adult_victim_count             82700 non-null   float64
 14  juvenile_victim_count          80063 non-null   float64
 15  total_offender_count           253776 non-null  int64
 16  adult_offender_count           73219 non-null   float64
 17  juvenile_offender_count        73212 non-null   float64
 18  offender_race                  253776 non-null  object
 19  offender_ethnicity             253776 non-null  object
 20  victim_count                   253776 non-null  int64
 21  offense_name                   253776 non-null  object
 22  total_individual_victims       248651 non-null  float64
 23  location_name                  253776 non-null  object
 24  bias_desc                      253776 non-null  object
 25  victim_types                   253776 non-null  object
 26  multiple_offense               253776 non-null  object
 27  multiple_bias                  253776 non-null  object
 28  crime_type                     253776 non-null  object
 29  year                           253776 non-null  int32
 30  area_type                      253776 non-null  object
 31  bias_category                  253776 non-null  object
dtypes: datetime64[ns](1), float64(5), int32(1), int64(4), object(21)
memory usage: 61.0+ MB
```

In [212…

```python
# Updating the selected features for One-Hot Encoding and Heatmap
one_hot_features = ["offender_ethnicity", "crime_type", "area_type", "agency_type_n

# Adding "bias_category" to One-Hot Encoding list
one_hot_features.append("bias_category")

numerical_features = [
    "victim_count", "juvenile_victim_count", "adult_victim_count",
    "total_individual_victims", "juvenile_offender_count",
    "adult_offender_count", "total_offender_count"
]

# Copy the dataset for encoding
df_encoded = df[numerical_features + one_hot_features].copy()

# Function to limit One-Hot Encoding to the Top 5 Most Frequent Categories
```

```
def limit_categories(df, column, top_n=6):
    top_categories = df[column].value_counts().nlargest(top_n).index
    df[column] = df[column].apply(lambda x: x if x in top_categories else "Other")
    return df

# Apply category limiting to One-Hot columns
for col in one_hot_features:
    df_encoded = limit_categories(df_encoded, col, top_n=5)

# Apply One-Hot Encoding to the selected categorical features
df_encoded = pd.get_dummies(df_encoded, columns=one_hot_features, drop_first=True)
```

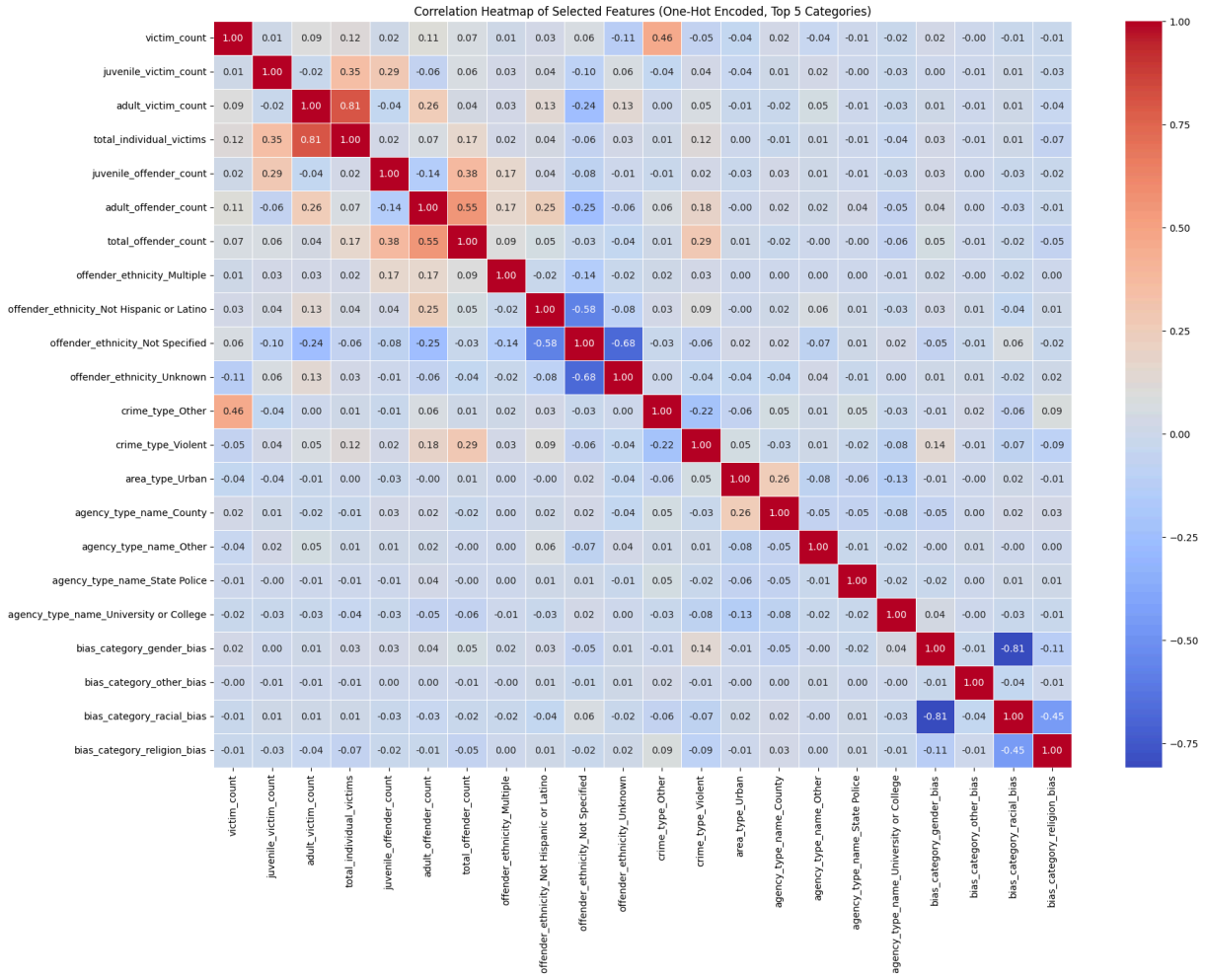
4. Features Selection

Correlation Matric with Pearson method (Default)

- Correlation Matric: Find out the highly correlated features with the selling prices (relavant independent features)

In [213…

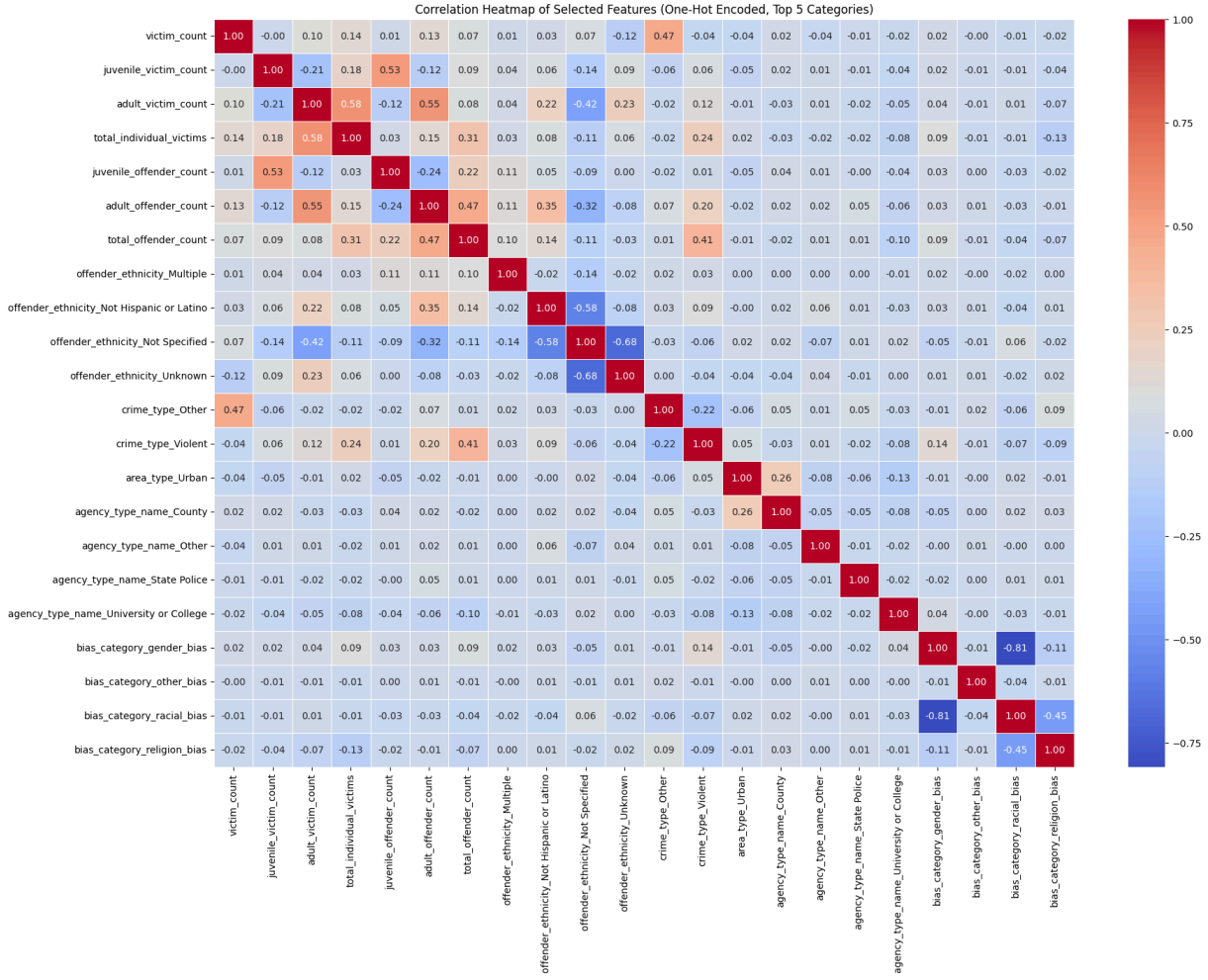
```
# Compute Correlation Heatmap
plt.figure(figsize=(20, 14))
sns.heatmap(df_encoded.corr(), cmap="coolwarm", annot=True, fmt=".2f", linewidths=0
plt.title("Correlation Heatmap of Selected Features (One-Hot Encoded, Top 5 Categor
plt.show()
```



Correlation Matrix with `Spearman` method: Good for non-linear relationship

In [214…

```
# Compute Correlation Heatmap
plt.figure(figsize=(20, 14))
sns.heatmap(df_encoded.corr(method='spearman'), cmap="coolwarm", annot=True, fmt=".
plt.title("Correlation Heatmap of Selected Features (One-Hot Encoded, Top 5 Categor
plt.show()
```



In [215…
```
print(df_encoded.columns)
```

```
Index(['victim_count', 'juvenile_victim_count', 'adult_victim_count',
       'total_individual_victims', 'juvenile_offender_count',
       'adult_offender_count', 'total_offender_count',
       'offender_ethnicity_Multiple',
       'offender_ethnicity_Not Hispanic or Latino',
       'offender_ethnicity_Not Specified', 'offender_ethnicity_Unknown',
       'crime_type_Other', 'crime_type_Violent', 'area_type_Urban',
       'agency_type_name_County', 'agency_type_name_Other',
       'agency_type_name_State Police',
       'agency_type_name_University or College', 'bias_category_gender_bias',
       'bias_category_other_bias', 'bias_category_racial_bias',
       'bias_category_religion_bias'],
      dtype='object')
```

Check Feature Importances

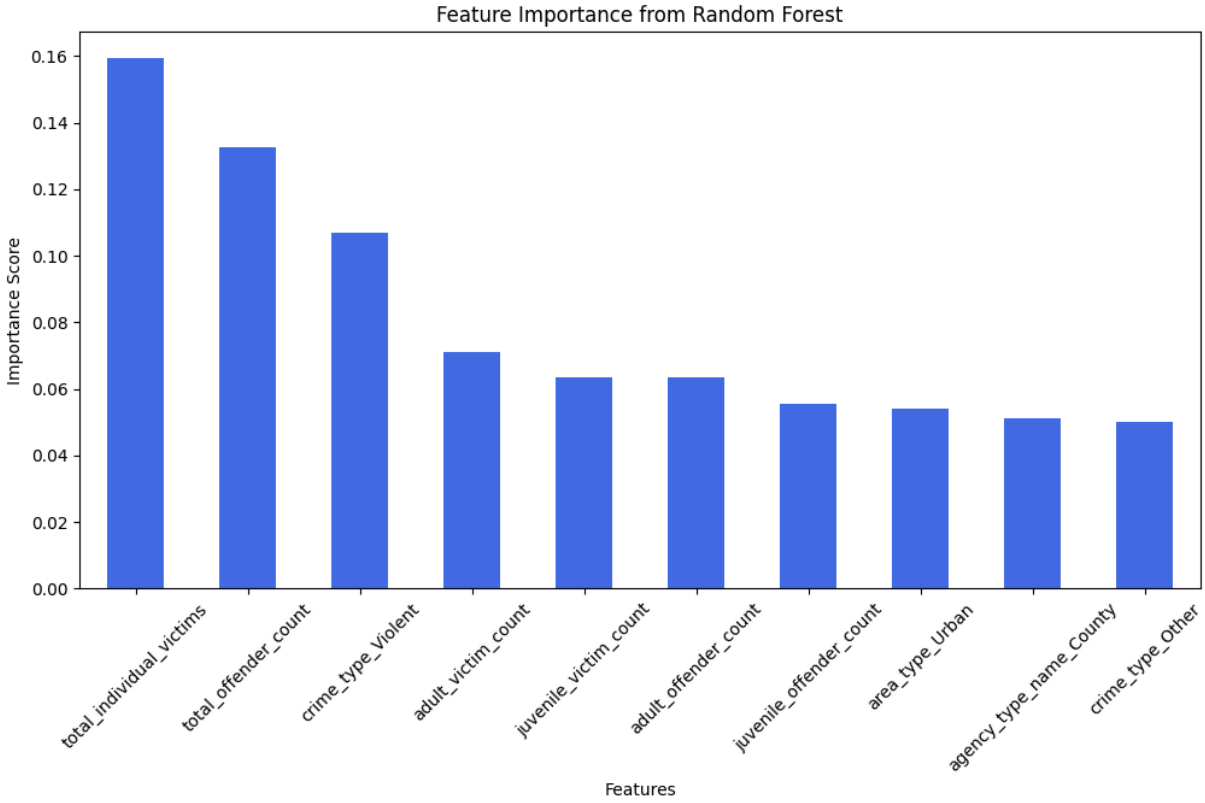
In [216…
```
# Check the correct column names
bias_columns = ["bias_category_racial_bias", "bias_category_gender_bias", "bias_cat

# Define features (X) and multi-label target (y)
X = df_encoded.drop(columns=bias_columns)  # Remove target columns
y = df_encoded[bias_columns]  # Multi-label target
```

```
print(X.columns)  # Ensure X has the correct features
print(y.columns)  # Ensure y has the correct labels
```

```
Index(['victim_count', 'juvenile_victim_count', 'adult_victim_count',
       'total_individual_victims', 'juvenile_offender_count',
       'adult_offender_count', 'total_offender_count',
       'offender_ethnicity_Multiple',
       'offender_ethnicity_Not Hispanic or Latino',
       'offender_ethnicity_Not Specified', 'offender_ethnicity_Unknown',
       'crime_type_Other', 'crime_type_Violent', 'area_type_Urban',
       'agency_type_name_County', 'agency_type_name_Other',
       'agency_type_name_State Police',
       'agency_type_name_University or College'],
      dtype='object')
Index(['bias_category_racial_bias', 'bias_category_gender_bias',
       'bias_category_other_bias', 'bias_category_religion_bias'],
      dtype='object')
```

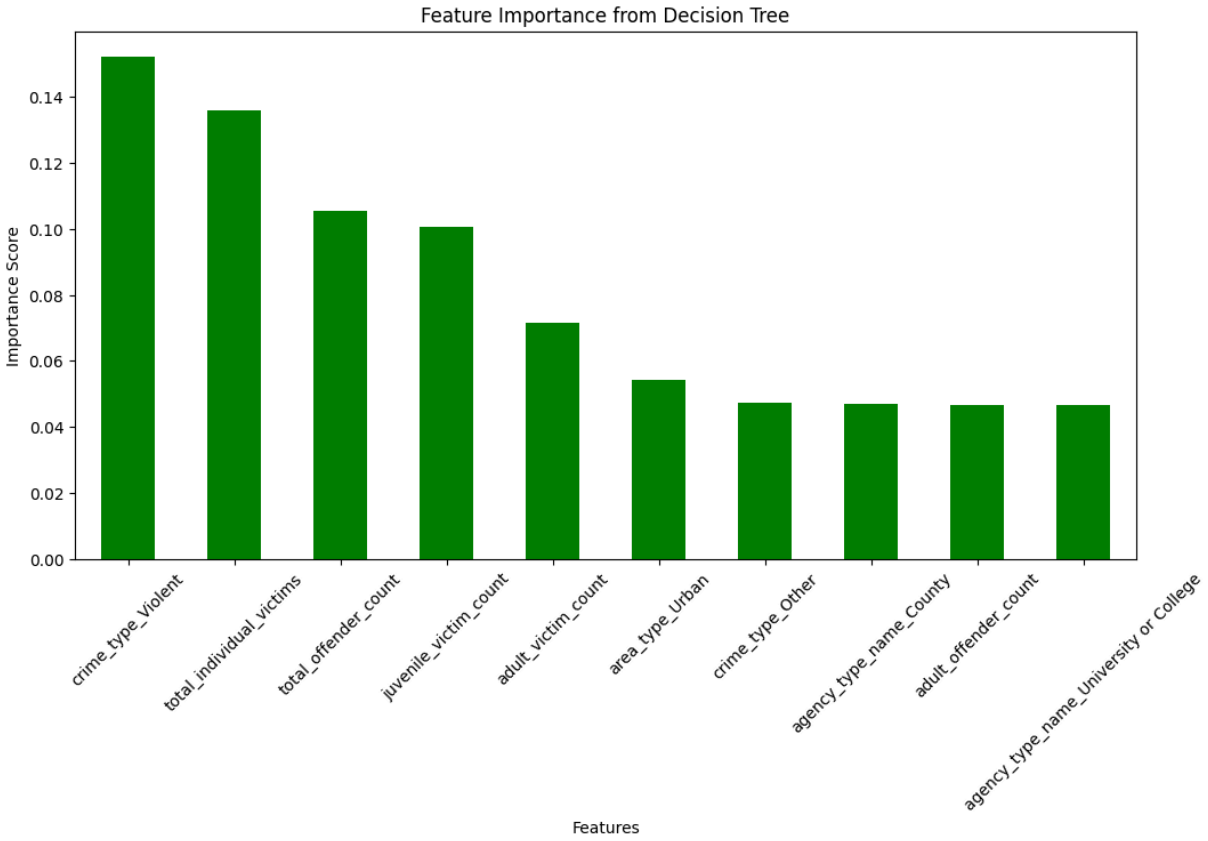
In [217…

```
from sklearn.ensemble import RandomForestClassifier
import matplotlib.pyplot as plt
import numpy as np

# Train a Random Forest model
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)

# Get feature importance
feature_importance = pd.Series(rf.feature_importances_, index=X.columns)

# Sort and visualize top features
plt.figure(figsize=(12, 6))
feature_importance.sort_values(ascending=False).head(10).plot(kind="bar", color="ro
plt.title("Feature Importance from Random Forest")
plt.ylabel("Importance Score")
plt.xlabel("Features")
plt.xticks(rotation=45)
plt.show()
```



In [218…

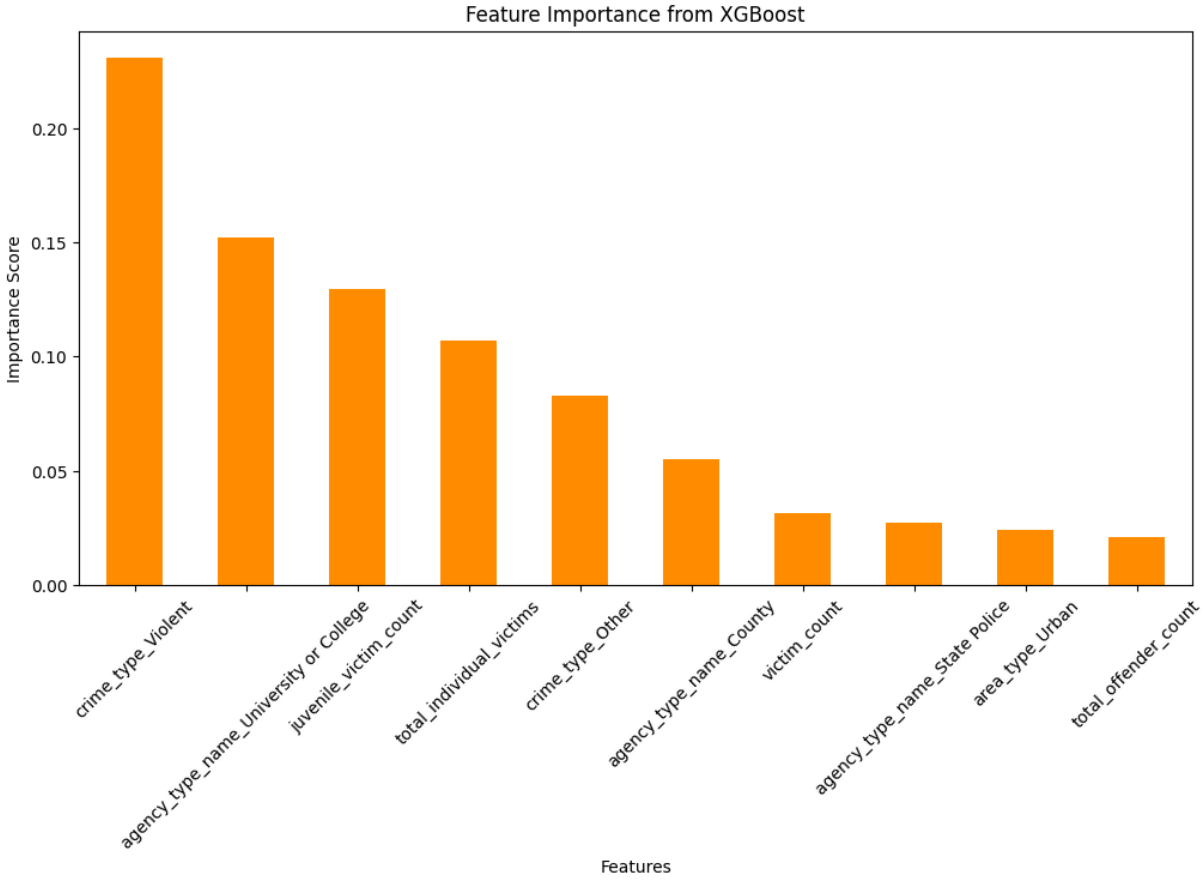
```
from sklearn.tree import DecisionTreeClassifier

# Train a Decision Tree model
dt = DecisionTreeClassifier(random_state=42)
dt.fit(X, y)

# Get feature importance
importances_dt = dt.feature_importances_

# Plot the feature importance
plt.figure(figsize=(12, 6))
(pd.Series(importances_dt, index=X.columns)
   .sort_values(ascending=False)
   .head(10)
   .plot(kind="bar", color="green"))
plt.title("Feature Importance from Decision Tree")
plt.ylabel("Importance Score")
plt.xlabel("Features")
plt.xticks(rotation=45)
plt.show()
```



In [220…

```
from xgboost import XGBClassifier
importances = {}

# Train an XGBoost model
xgb = XGBClassifier(n_estimators=100, random_state=42, use_label_encoder=False, eva
xgb.fit(X, y)

# Get feature importance
importances["XGBoost"] = xgb.feature_importances_

# Plot the feature importance
plt.figure(figsize=(12, 6))
(pd.Series(importances["XGBoost"], index=X.columns)
   .sort_values(ascending=False)
   .head(10)
   .plot(kind="bar", color="darkorange"))
plt.title("Feature Importance from XGBoost")
plt.ylabel("Importance Score")
plt.xlabel("Features")
plt.xticks(rotation=45)
plt.show()
```

```
c:\Users\Legion 5 Pro\AppData\Local\Programs\Python\Python311\Lib\site-packages\xgbo
ost\training.py:183: UserWarning: [21:05:18] WARNING: C:\actions-runner\_work\xgboos
t\xgboost\src\learner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```



`Our target variable is bias_desc`

Best Candidates Algorithms:

- Random Forest → Handles high-dimensional data well, less overfitting than DT
- XGBoost → Extremely powerful, but requires fine-tuning
- Decision Tree → One of the most powerful model, but can be overfitting.

Selected Features and Justification

1. `total_offender_count`

- Ranked highly in both Random Forest and Decision Tree feature importance.
- Strongly correlated with variables like adult_offender_count and juvenile_offender_count in the heatmap.
- Represents the scale of the offense, indicating group involvement or organized activity, which is crucial for analyzing hate crime severity.

2. `total_individual_victims`

- Received the highest importance score in the Random Forest model.

- Reflects the impact and magnitude of harm done in a hate crime incident.
- Strongly indicative of the overall seriousness of the case and valuable for prediction.

3. `crime_type_violent`

- Top-ranked in the Decision Tree model and among the top 3 in Random Forest.
- Correlates well with adult_victim_count and juvenile_victim_count, showing its influence.
- Acts as a key classifier to distinguish between violent and non-violent crimes — critical in hate crime categorization.

4. `area_type_Urban`

- Represents the geographical context of the incident (urban vs. rural).
- While not the most dominant feature, it consistently appears in the top 10 in both models.
- Urban areas often have higher population diversity and density, which may correlate with the frequency and types of hate crimes.

My final verdict for features selection

These four features were chosen because they balance statistical significance (via correlation and model importance) with real-world interpretability.

Together, they provide strong predictive power and meaningful insights into the nature and context of hate crime data.