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DSC 680

Final Project 3

Hate Crimes in the US

Background/History and our Business Problem

```
According to recent FBI reports, dat from as recent as 2022 tells us that the current rate of hate crimes in the
country has been increasing in the past years (2022 FBI hate crimes statistics 2023). Race related hate crimes are
among the highest rate of hate crimes committed in the country with religion and anti-LGBTQ hate crimes being other
major motivations for such crimes as well. Hate crimes are both a social as well as a political problem. While a lot
of hate crimes are politically motivated, above everything else, they are still crimes that affect society as a whole.
For that reason, we dive into our investigation.

The main problem that we want to investigate during this research project is to have some sort of analysis of hate
crimes being committed in the USA. We want to be able to answer questions such as the following:

What are the different motivations for hate crimes?
Is there one type of hate crime more common than others?
Are there any trends in hate crimes in the country? (increasing? decreasing? Who is safe and who isn’t)
What type of hate crimes are most common and where? (if specific locations apply)

We also want to be able to create a model to determine what type of hate crime is most likely to happen given specific
conditions in order to get a better idea of hate crime demographics in the future.
```

Data Explanation (Data Prep, Data Dictionary, etc)

```
The data that we will be using a data set found on Kaggle.com titled
"hate_crime_usa".
The data set contains information and records for 209442 different ha
te crimes that have been reported by the FBI.
It's important to note that hate crimes and crime in general tends to
have a hidden figure, often refered to the
"dark figure of crime". A lot of crime, espeicially crimes towards ma
rginalized communties often go unreported due
to the lack of support those communities face.

Originally, our data set contains 28 different varaibles.

INCIDENT_ID--------------Identifying number given to each incident re
port
DATA_YEAR----------------The year of the incident report
ORI----------------------Organization Record Identifier
PUB_AGENCY_NAME----------Public agency name in which the crime was re
ported
PUB_AGENCY_UNIT----------Unit of that public agency
STATE_ABBR---------------State abbrivation of the incident
STATE_NAME---------------Full name of the state in which the indicent
happened
DIVISION_NAME------------Name of the division in which the incident w
as reported
REGION_NAME--------------The region of the country
POPULATION_GROUP_CODE----Population assigned descriptions
POPULATION_GROUP_DESC----Generic size of the population
INCIDENT_DATE------------Date of the Incident
ADULT_VICTIM_COUNT-------Amount of Adult Victims
JUVENILE_VICTIM_COUNT----Amount of Minor Victimes
TOTAL_OFFENDER_COUNT-----Amount of Offenders
ADULT_OFFENDER_COUNT-----Amount of Adult Offenders
JUVENILE_OFFENDER_COUNT--Amount of Minor Offenders
OFFENDER_RACE------------Race of the Offender
OFFENDER_ETHNICITY-------Ethnicity of Offender
VICTIM_COUNT-------------Amount of Victims
OFFENSE_NAME-------------Name of the Offfense
TOTAL_INDIVIDUAL_VICTIMS-Total individual Victim Count
LOCATION_NAME------------Location type of incident
BIAS_DESC----------------Reason for Hate Crime (Marginalized Group_
VICTIM_TYPES-------------Type of Victim (individual, group, organizat
ion etc.)
MULTIPLE_OFFENSE---------Offender committed multiple offenses? (Singu
lar or Multiple)
MULTIPLE_BIAS------------Offender committed crime based on multiple b
iases? (Singular or Multiple)
```

Importing Data and Main Packages

Before we can begin to build our model we must first load our data. A
view of what the data looks like can be found

In [2]:
```
#Importing Data and Packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

hcrime = pd.read_csv('hate_crime.csv')
hcrime = pd.DataFrame(hcrime)
orig_data = hcrime
hcrime
```

```
C:\Users\nickx\AppData\Local\Temp\ipykernel_6864\1073563014.py:6: DtypeWarnin
g: Columns (19) have mixed types. Specify dtype option on import or set low_m
emory=False.
  hcrime = pd.read_csv('hate_crime.csv')
```

Out[2]:

	INCIDENT_ID	DATA_YEAR	ORI	PUB_AGENCY_NAME	PUB_AGENCY_UNIT	AGE
0	3015	1991	AR0040200	Rogers	NaN	
1	3016	1991	AR0290100	Hope	NaN	
2	43	1991	AR0350100	Pine Bluff	NaN	
3	44	1991	AR0350100	Pine Bluff	NaN	
4	3017	1991	AR0350100	Pine Bluff	NaN	
...	...	...	...	...	...	
209437	558879	2019	WY0010100	Laramie	NaN	
209438	558880	2019	WY0010200	University of Wyoming	NaN	
209439	661208	2019	WY0150100	Cody	NaN	
209440	463806	2019	WY0170100	Sheridan	NaN	
209441	705012	2019	WY0210100	Evanston	NaN	

209442 rows × 28 columns

Examining and Cleaning Data

```
Once our data has been loaded and saved in a dataframe, we can start examining the data more closely. Then we can
see what we need to do in order to clean and prepare the data for our analysis.

The first thing that we did was get rid of a few varaibles. The variables we chose to get rid of were eitehr redundant,
not useful for our investigation, or simply didn't make sense to keep in our model based on our analysis goals. The
varaibles we chose to get rid of were the following:

PUB_AGENCY_NAME, PUB_AGENCY_UNIT, AGENCY_TYPE_NAME, DIVISION_NAME, POPULATION_GROUP_CODE, INCIDENT_DATE,
ADULT_VICTIM_COUNT, JUVENILE_VICTIM_COUNT, ADULT_OFFENDER_COUNT, ORI, JUVENILE_OFFENDER_COUNT, OFFENDER_ETHNICITY,
TOTAL_INDIVIDUAL_VICTIMS, and INCIDENT_ID.
```

In [3]:
```
#Getting rid of columns we aren't interested in:

hcrime = hcrime.drop(['PUB_AGENCY_NAME', 'PUB_AGENCY_UNIT', 'AGENCY_TYPE_NAME'
                      'INCIDENT_DATE', 'ADULT_VICTIM_COUNT', 'JUVENILE_VICTIM_C
                      'JUVENILE_OFFENDER_COUNT', 'OFFENDER_ETHNICITY', 'TOTAL_I
hcrime
```

Out[3]:

	DATA_YEAR	STATE_ABBR	STATE_NAME	REGION_NAME	POPULATION_GROUP_DESC
0	1991	AR	Arkansas	South	Cities from 10,000 thru 24,999
1	1991	AR	Arkansas	South	Cities from 2,500 thru 9,999
2	1991	AR	Arkansas	South	Cities from 50,000 thru 99,999
3	1991	AR	Arkansas	South	Cities from 50,000 thru 99,999
4	1991	AR	Arkansas	South	Cities from 50,000 thru 99,999
...	...	...	...	...	...
209437	2019	WY	Wyoming	West	Cities from 25,000 thru 49,999
209438	2019	WY	Wyoming	West	Cities under 2,500
209439	2019	WY	Wyoming	West	Cities from 2,500 thru 9,999
209440	2019	WY	Wyoming	West	Cities from 10,000 thru 24,999
209441	2019	WY	Wyoming	West	Cities from 10,000 thru 24,999

209442 rows × 14 columns

```
In addition to getting rid on unecessary columns, we also want to dou
ble check that there are no duplicates or
missing values in our data.
```

In [4]:
```
#Cleaning data: Rid of duplicates and missing values

hcrime = hcrime.drop_duplicates()
hcrime = hcrime.dropna()
hcrime
```

Out[4]:

	DATA_YEAR	STATE_ABBR	STATE_NAME	REGION_NAME	POPULATION_GROUP_DESC
0	1991	AR	Arkansas	South	Cities from 10,000 thru 24,999
1	1991	AR	Arkansas	South	Cities from 2,500 thru 9,999
2	1991	AR	Arkansas	South	Cities from 50,000 thru 99,999
3	1991	AR	Arkansas	South	Cities from 50,000 thru 99,999
4	1991	AR	Arkansas	South	Cities from 50,000 thru 99,999
...	...	...	...	...	...
209437	2019	WY	Wyoming	West	Cities from 25,000 thru 49,999
209438	2019	WY	Wyoming	West	Cities under 2,500
209439	2019	WY	Wyoming	West	Cities from 2,500 thru 9,999
209440	2019	WY	Wyoming	West	Cities from 10,000 thru 24,999
209441	2019	WY	Wyoming	West	Cities from 10,000 thru 24,999

169761 rows × 14 columns

```
In this next portion of the code we want to see all the different uni
que values for each of the categorical
variables, which would be all of our predicting varaibles. This will
help us decide if there are any other varaibles
that we might want to consider getting rid of before moving onto our
model-building process. We can also get an idea
of all the different types of unique values for each variable as well
as the spread in terms of frequency of those
values.
```

In [5]:
```
#Unique Values for STATE_ABBR
print(hcrime['STATE_ABBR'].value_counts())
```

```
STATE_ABBR
CA    27724
NJ    12013
MI    10627
MA     9028
NY     8488
OH     7438
WA     7411
TX     7270
AZ     5663
VA     4991
IL     4838
FL     4583
MN     4133
MD     3953
OR     3930
CO     3887
TN     3713
CT     3347
KY     3075
MO     2843
PA     2795
NC     2365
SC     1916
IN     1756
KS     1631
UT     1595
NV     1518
WI     1439
DC     1356
OK     1302
ME     1176
ID     1171
AR     1018
GA      963
NB      929
WV      863
RI      805
DE      797
IA      778
MT      651
NH      599
SD      542
NM      523
LA      512
VT      496
ND      406
AK      219
AL      205
MS      169
WY      142
HI       85
FS       79
GM        5
Name: count, dtype: int64
```

In [6]:
```
#Unique Values for STATE_NAME
print(hcrime['STATE_NAME'].value_counts())
```

```
STATE_NAME
California              27724
New Jersey              12013
Michigan                10627
Massachusetts            9028
New York                 8488
Ohio                     7438
Washington               7411
Texas                    7270
Arizona                  5663
Virginia                 4991
Illinois                 4838
Florida                  4583
Minnesota                4133
Maryland                 3953
Oregon                   3930
Colorado                 3887
Tennessee                3713
Connecticut              3347
Kentucky                 3075
Missouri                 2843
Pennsylvania             2795
North Carolina           2365
South Carolina           1916
Indiana                  1756
Kansas                   1631
Utah                     1595
Nevada                   1518
Wisconsin                1439
District of Columbia     1356
Oklahoma                 1302
Maine                    1176
Idaho                    1171
Arkansas                 1018
Georgia                   963
Nebraska                  929
West Virginia             863
Rhode Island              805
Delaware                  797
Iowa                      778
Montana                   651
New Hampshire             599
South Dakota              542
New Mexico                523
Louisiana                 512
Vermont                   496
North Dakota              406
Alaska                    219
Alabama                   205
Mississippi               169
Wyoming                   142
Hawaii                     85
Federal                    79
Guam                        5
Name: count, dtype: int64
```

In [7]:
```
#Unique Values for REGION_NAME
print(hcrime['REGION_NAME'].value_counts())
```

```
REGION_NAME
West                 54519
South                39051
Northeast            38747
Midwest              37360
Other                   79
U.S. Territories         5
Name: count, dtype: int64
```

In [8]:
```
#Unique Values for POPULATION_GROUP_DESC
print(hcrime['POPULATION_GROUP_DESC'].value_counts())
```

```
POPULATION_GROUP_DESC
Cities from 50,000 thru 99,999
20079
Cities from 25,000 thru 49,999
19254
Cities 1,000,000 or over
18775
Cities from 100,000 thru 249,999
17756
Cities from 500,000 thru 999,999
17515
Cities from 10,000 thru 24,999
16755
MSA counties 100,000 or over
14030
Cities from 250,000 thru 499,999
13257
Cities from 2,500 thru 9,999
10886
Cities under 2,500
9103
MSA counties from 25,000 thru 99,999
4983
Non-MSA counties from 25,000 thru 99,999
1757
Non-MSA counties from 10,000 thru 24,999
1751
Non-MSA counties under 10,000
1334
MSA counties under 10,000
1288
MSA counties from 10,000 thru 24,999
854
Non-MSA counties 100,000 or over
202
Non-MSA State Police
151
MSA State Police
26
Possessions (Puerto Rico, Guam, Canal Zone, Virgin Islands, and American Samo
a)         5
Name: count, dtype: int64
```

In [9]:
```
#Unique Values for OFFENDER_RACE
print(hcrime['OFFENDER_RACE'].value_counts())
```

```
OFFENDER_RACE
White                                        71449
Unknown                                      67299
Black or African American                    24269
Multiple                                      4092
Asian                                         1474
American Indian or Alaska Native              1127
Native Hawaiian or Other Pacific Islander       51
Name: count, dtype: int64
```

In [10]:
```
#Unique Values for OFFENSE_NAME
print(hcrime['OFFENSE_NAME'].value_counts())
```

```
OFFENSE_NAME
Intimidation
47673
Destruction/Damage/Vandalism of Property
45808
Simple Assault
34947
Aggravated Assault
19735
Robbery
3364

...
Intimidation;Motor Vehicle Theft;Robbery;Simple Assault
1
Aggravated Assault;Destruction/Damage/Vandalism of Property;Fondling
1
Destruction/Damage/Vandalism of Property;Intimidation;Theft of Motor Vehicle
Parts or Accessories        1
Burglary/Breaking & Entering;Motor Vehicle Theft;Robbery
1
Drug/Narcotic Violations;Robbery
1
Name: count, Length: 344, dtype: int64
```

In [11]:
```
#Unique Values for LOCATION_NAME
print(hcrime['LOCATION_NAME'].value_counts())
```

```
LOCATION_NAME
Residence/Home                                                              4
8166
Highway/Road/Alley/Street/Sidewalk                                          3
3496
Other/Unknown                                                               1
7201
School/College                                                              1
3587
Parking/Drop Lot/Garage                                                     1
1068

...
Drug Store/Doctor's Office/Hospital;Parking/Drop Lot/Garage
1
Convenience Store;Jail/Prison/Penitentiary/Corrections Facility
1
Church/Synagogue/Temple/Mosque;Highway/Road/Alley/Street/Sidewalk
1
Government/Public Building;Jail/Prison/Penitentiary/Corrections Facility
1
Air/Bus/Train Terminal;School-Elementary/Secondary
1
Name: count, Length: 123, dtype: int64
```

In [12]:
```
#Unique Values for BIAS_DESC
print(hcrime['BIAS_DESC'].value_counts())
```

```
BIAS_DESC
Anti-Black or African American
54612
Anti-White
21373
Anti-Gay (Male)
18065
Anti-Jewish
15712
Anti-Hispanic or Latino
12132

...
Anti-Arab;Anti-Asian;Anti-Black or African American
1
Anti-Male;Anti-Native Hawaiian or Other Pacific Islander
1
Anti-Mental Disability;Anti-Other Race/Ethnicity/Ancestry
1
Anti-Gay (Male);Anti-Heterosexual
1
Anti-Black or African American;Anti-Hispanic or Latino;Anti-Multiple Races, G
roup        1
Name: count, Length: 217, dtype: int64
```

In [13]:
```
#Unique Values for VICTIM_TYPES
print(hcrime['VICTIM_TYPES'].value_counts())
```

```
VICTIM_TYPES
Individual                                             139461
Business                                                 7848
Other                                                    6741
Religious Organization                                   4555
Government                                               4277
Society/Public                                           3272
Individual;Other                                          931
Business;Individual                                       778
Unknown                                                   720
Individual;Society/Public                                 342
Government;Individual                                     188
Individual;Religious Organization                         176
Law Enforcement Officer                                   117
Financial Institution                                      89
Individual;Unknown                                         50
Business;Government                                        36
Individual;Law Enforcement Officer                         31
Business;Society/Public                                    20
Business;Unknown                                           18
Business;Government;Individual                             16
Business;Religious Organization                            13
Government;Religious Organization                          10
Business;Other                                              9
Business;Individual;Religious Organization                  7
Government;Society/Public                                   6
Government;Individual;Religious Organization                5
Religious Organization;Society/Public                       5
Financial Institution;Individual                            3
Government;Other                                            3
Other;Religious Organization                                3
Business;Individual;Society/Public                          3
Society/Public;Unknown                                      2
Business;Financial Institution                              2
Government;Individual;Society/Public                        2
Business;Government;Religious Organization                  2
Law Enforcement Officer;Society/Public                      2
Government;Law Enforcement Officer                          2
Government;Unknown                                          1
Financial Institution;Individual;Society/Public             1
Government;Individual;Law Enforcement Officer               1
Financial Institution;Government                            1
Law Enforcement Officer;Unknown                             1
Financial Institution;Other;Society/Public;Unknown          1
Other;Society/Public                                        1
Business;Financial Institution;Individual                   1
Business;Financial Institution;Government;Other             1
Individual;Other;Religious Organization                     1
Business;Government;Individual;Other                        1
Business;Individual;Unknown                                 1
Business;Government;Individual;Religious Organization       1
Government;Individual;Other;Religious Organization          1
Business;Individual;Other                                   1
Individual;Religious Organization;Society/Public            1
Name: count, dtype: int64
```

In [14]:
```
#Unique Values for MULTIPLE_OFFENSE
print(hcrime['MULTIPLE_OFFENSE'].value_counts())
```

```
MULTIPLE_OFFENSE
S    161291
M      8470
Name: count, dtype: int64
```

In [15]:
```
#Unique Values for MULTIPLE_BIAS
print(hcrime['MULTIPLE_BIAS'].value_counts())
```

```
MULTIPLE_BIAS
S    169124
M       637
Name: count, dtype: int64
```

In [16]:
```
#Getting rid of "noise": Getting rid of crime location that happened less than

# Get the frequency of each value in the 'A' column
counts = hcrime['LOCATION_NAME'].value_counts()

# Remove observations with frequency of 1
hcrime = hcrime[~hcrime['LOCATION_NAME'].isin(counts[counts <= 100].index)]
print(hcrime['LOCATION_NAME'].value_counts())
```

```
LOCATION_NAME
Residence/Home                                       48166
Highway/Road/Alley/Street/Sidewalk                   33496
Other/Unknown                                        17201
School/College                                       13587
Parking/Drop Lot/Garage                              11068
Church/Synagogue/Temple/Mosque                        6369
Commercial/Office Building                            4371
Restaurant                                            4087
Bar/Nightclub                                         3635
Government/Public Building                            2835
Convenience Store                                     2606
Specialty Store                                       2220
School-Elementary/Secondary                           2132
Field/Woods                                           1935
Air/Bus/Train Terminal                                1919
Service/Gas Station                                   1879
Grocery/Supermarket                                   1687
Department/Discount Store                             1596
Drug Store/Doctor's Office/Hospital                   1462
Jail/Prison/Penitentiary/Corrections Facility         1311
Hotel/Motel/Etc.                                      1255
School-College/University                             1166
Park/Playground                                        828
Construction Site                                      516
Bank/Savings and Loan                                  439
Liquor Store                                           371
Lake/Waterway/Beach                                    342
Rental Storage Facility                                196
Shopping Mall                                          156
Name: count, dtype: int64
```

In [17]:
```
#Getting rid of "noise": Getting rid of offenses that happened less than 100 t

# Get the frequency of each value in the 'A' column
counts = hcrime['OFFENSE_NAME'].value_counts()

# Remove observations with frequency of 1
hcrime = hcrime[~hcrime['OFFENSE_NAME'].isin(counts[counts <= 100].index)]
print(hcrime['OFFENSE_NAME'].value_counts())
```

```
OFFENSE_NAME
Intimidation                                                              4744
9
Destruction/Damage/Vandalism of Property                                  4565
6
Simple Assault                                                            3478
8
Aggravated Assault                                                        1968
2
Robbery                                                                    335
9
Burglary/Breaking & Entering                                               259
7
Destruction/Damage/Vandalism of Property;Intimidation                      168
6
All Other Larceny                                                          164
1
Arson                                                                      107
1
Intimidation;Simple Assault                                                 82
8
Drug/Narcotic Violations                                                    75
8
Not Specified                                                               63
7
Theft From Motor Vehicle                                                    59
3
Shoplifting                                                                 52
9
Burglary/Breaking & Entering;Destruction/Damage/Vandalism of Property       51
0
Destruction/Damage/Vandalism of Property;Simple Assault                     50
1
Aggravated Assault;Intimidation                                             48
6
Theft From Building                                                         46
8
Motor Vehicle Theft                                                         38
5
Aggravated Assault;Destruction/Damage/Vandalism of Property                 36
6
Aggravated Assault;Simple Assault                                           33
4
Weapon Law Violations                                                       29
9
Murder and Nonnegligent Manslaughter                                        24
6
False Pretenses/Swindle/Confidence Game                                     23
8
Rape                                                                        23
7
Drug Equipment Violations                                                   23
3
Counterfeiting/Forgery                                                      18
4
Theft of Motor Vehicle Parts or Accessories                                 16
0
```

```
Fondling                                                       15
6
Aggravated Assault;Robbery                                     13
3
Credit Card/Automated Teller Machine Fraud                     12
7
Destruction/Damage/Vandalism of Property;Not Specified         12
2
Impersonation                                                  10
5
Name: count, dtype: int64
```

In [18]:
```
#Getting rid of "noise": Getting rid of offenses that happened less than 100 t

# Get the frequency of each value in the 'A' column
counts = hcrime['OFFENSE_NAME'].value_counts()

# Remove observations with frequency of 1
hcrime = hcrime[~hcrime['OFFENSE_NAME'].isin(counts[counts <= 100].index)]
print(hcrime['OFFENSE_NAME'].value_counts())
```

```
OFFENSE_NAME
Intimidation                                                              4744
9
Destruction/Damage/Vandalism of Property                                  4565
6
Simple Assault                                                            3478
8
Aggravated Assault                                                        1968
2
Robbery                                                                    335
9
Burglary/Breaking & Entering                                               259
7
Destruction/Damage/Vandalism of Property;Intimidation                      168
6
All Other Larceny                                                          164
1
Arson                                                                      107
1
Intimidation;Simple Assault                                                 82
8
Drug/Narcotic Violations                                                    75
8
Not Specified                                                               63
7
Theft From Motor Vehicle                                                    59
3
Shoplifting                                                                 52
9
Burglary/Breaking & Entering;Destruction/Damage/Vandalism of Property       51
0
Destruction/Damage/Vandalism of Property;Simple Assault                     50
1
Aggravated Assault;Intimidation                                             48
6
Theft From Building                                                         46
8
Motor Vehicle Theft                                                         38
5
Aggravated Assault;Destruction/Damage/Vandalism of Property                 36
6
Aggravated Assault;Simple Assault                                           33
4
Weapon Law Violations                                                       29
9
Murder and Nonnegligent Manslaughter                                        24
6
False Pretenses/Swindle/Confidence Game                                     23
8
Rape                                                                        23
7
Drug Equipment Violations                                                   23
3
Counterfeiting/Forgery                                                      18
4
Theft of Motor Vehicle Parts or Accessories                                 16
0
```

```
Fondling                                                            15
6
Aggravated Assault;Robbery                                          13
3
Credit Card/Automated Teller Machine Fraud                          12
7
Destruction/Damage/Vandalism of Property;Not Specified              12
2
Impersonation                                                       10
5
Name: count, dtype: int64
```

```
We use the results above to first decide to get rid of one of the sta
te columns since they both say the same thing. We
also decide that we want to get rid of the instances of multiple bias
offenses since we want to be able to predict just
one type of bias. On top of that we decide to get rid of a few observ
ations to not only make each category more balanced
but to make sure that the variables that we do use have a significant
amount of observation per cateogry. For example,
we wouldn't want to concern ourselves too much with offenses that do
n't happen as often. We have to consider that these
incident reports are crimes reported within the last 30+ years. Meani
ng that crimes that happened less than 100 times
in that span of time would have only occured about 3 times a year.
```

In [19]:
```
hcrime = hcrime.drop(['STATE_NAME'], axis=1)

# Drop all rows where MULTIPLE_BIAS = M
hcrime = hcrime.drop(hcrime[hcrime['MULTIPLE_BIAS'] == 'M'].index)

#Drop MULTIPLE_BIAS since we now know there is only singular bias for each obs
hcrime = hcrime.drop(['MULTIPLE_BIAS'], axis=1)
hcrime
```

Out[19]:

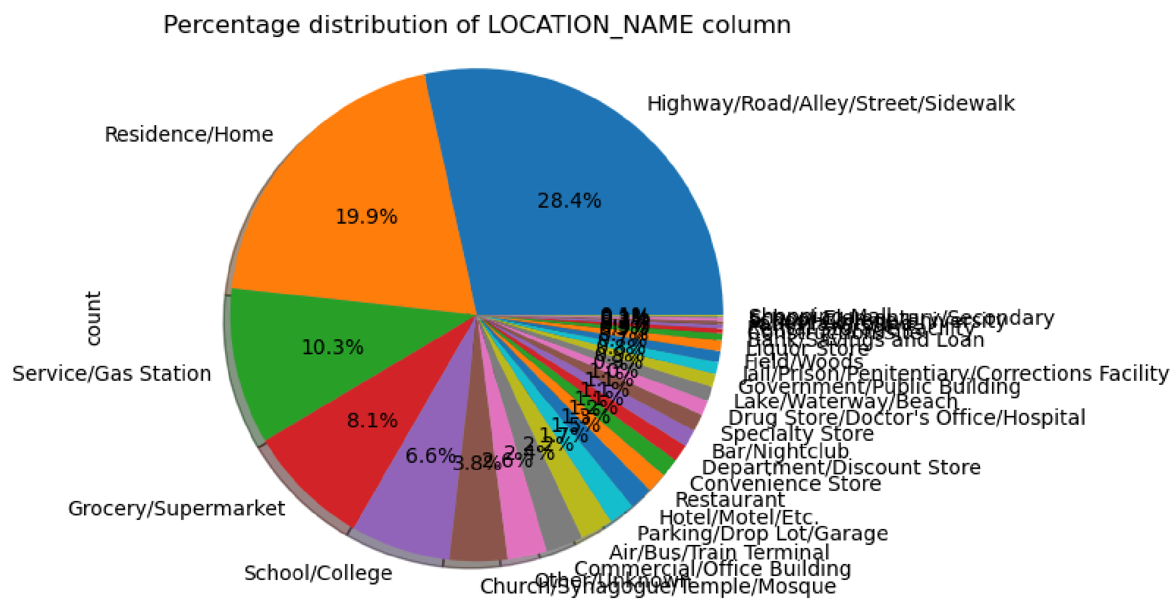
	DATA_YEAR	STATE_ABBR	REGION_NAME	POPULATION_GROUP_DESC	TOTAL_OFFEN
0	1991	AR	South	Cities from 10,000 thru 24,999	
1	1991	AR	South	Cities from 2,500 thru 9,999	
2	1991	AR	South	Cities from 50,000 thru 99,999	
3	1991	AR	South	Cities from 50,000 thru 99,999	
4	1991	AR	South	Cities from 50,000 thru 99,999	
...	...	...	...	...	
209437	2019	WY	West	Cities from 25,000 thru 49,999	
209438	2019	WY	West	Cities under 2,500	
209439	2019	WY	West	Cities from 2,500 thru 9,999	
209440	2019	WY	West	Cities from 10,000 thru 24,999	
209441	2019	WY	West	Cities from 10,000 thru 24,999	

165999 rows × 12 columns

Data Exploration:

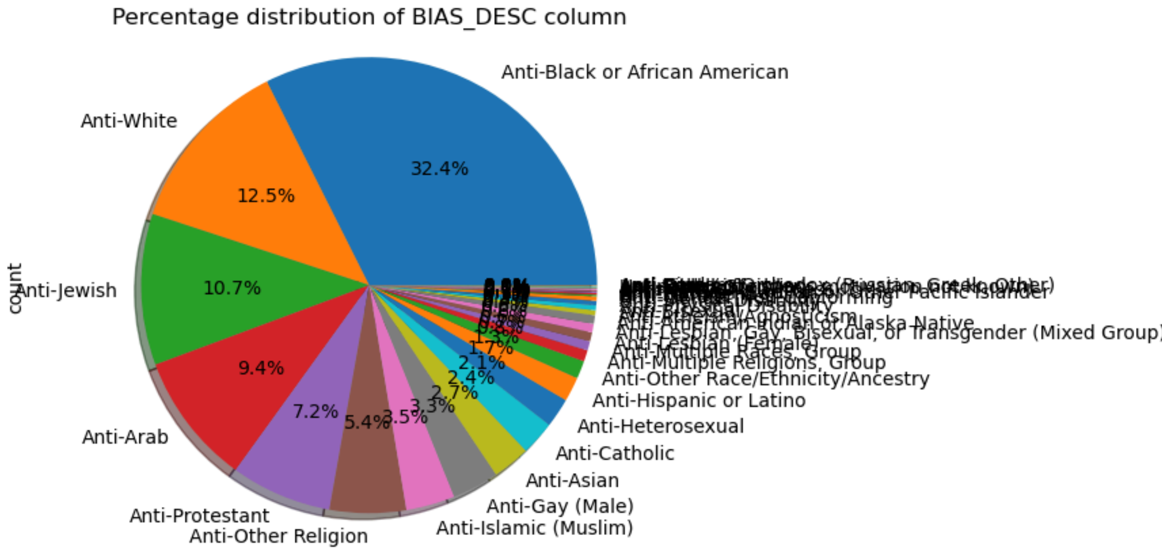
```
Now, from the cleaning phase of our analysis we move onto our data ex
ploration phase. Here we look at the distribution
of different cateogircal variables including our target varaible for
our analaysis. In total we looked at seven
differentcategorical varaible pie charts but for our analysis here we
only include one pie chart for our target
varaiable (OFFENSE_NAME) and two pie charts for two of our predicting
varaibles (LOCATION_NAME and BIAS_DESC). The
remaining pie charts can be found in our appendix, although the resul
ts will be written bellow the visuals.

In addition to exploring our cateogrical variables, we also look at t
he incident report numbers over the years on a
histogram where we can see the amount of hate crimes committed each y
ear.
```

In [20]:
```
#Percentage Pie Chart of Crime Rates in different Locations
counts = hcrime['LOCATION_NAME'].value_counts()
labels = hcrime.LOCATION_NAME.unique()
counts.plot.pie(autopct='%1.1f%%', labels= labels, shadow=True)

plt.title('Percentage distribution of LOCATION_NAME column')

plt.axis('equal')
plt.show()
```



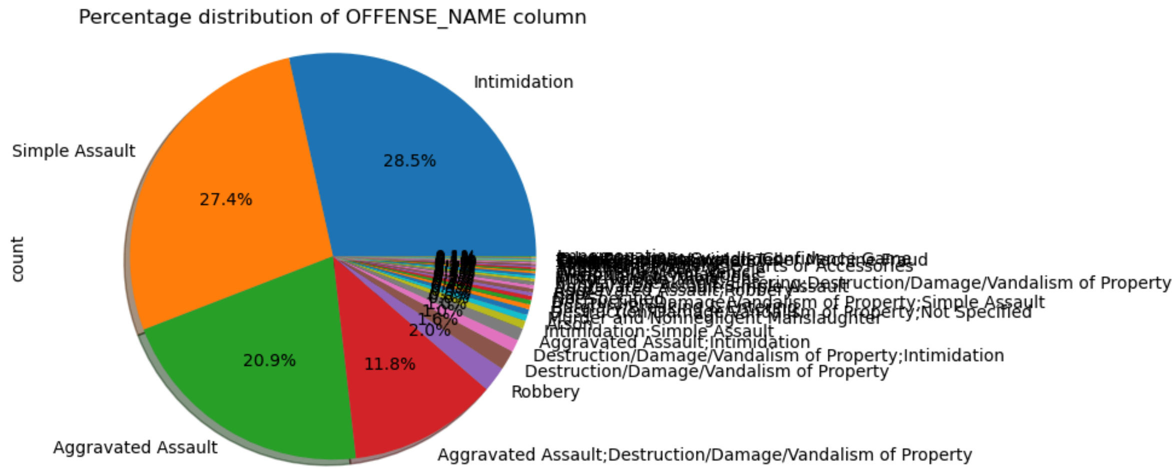

```
Here we can see that the majority of hate crimes out of the incidents
reported occured on some kind of highway, road
alleyway or sidewalk. More than a quarter to be exact.
```

In [21]:
```
#Percentage Pie Chart of Crime Rates in different bias descriptions
counts = hcrime['BIAS_DESC'].value_counts()
labels = hcrime.BIAS_DESC.unique()
counts.plot.pie(autopct='%1.1f%%', labels= labels, shadow=True)

plt.title('Percentage distribution of BIAS_DESC column')

plt.axis('equal')
plt.show()
```



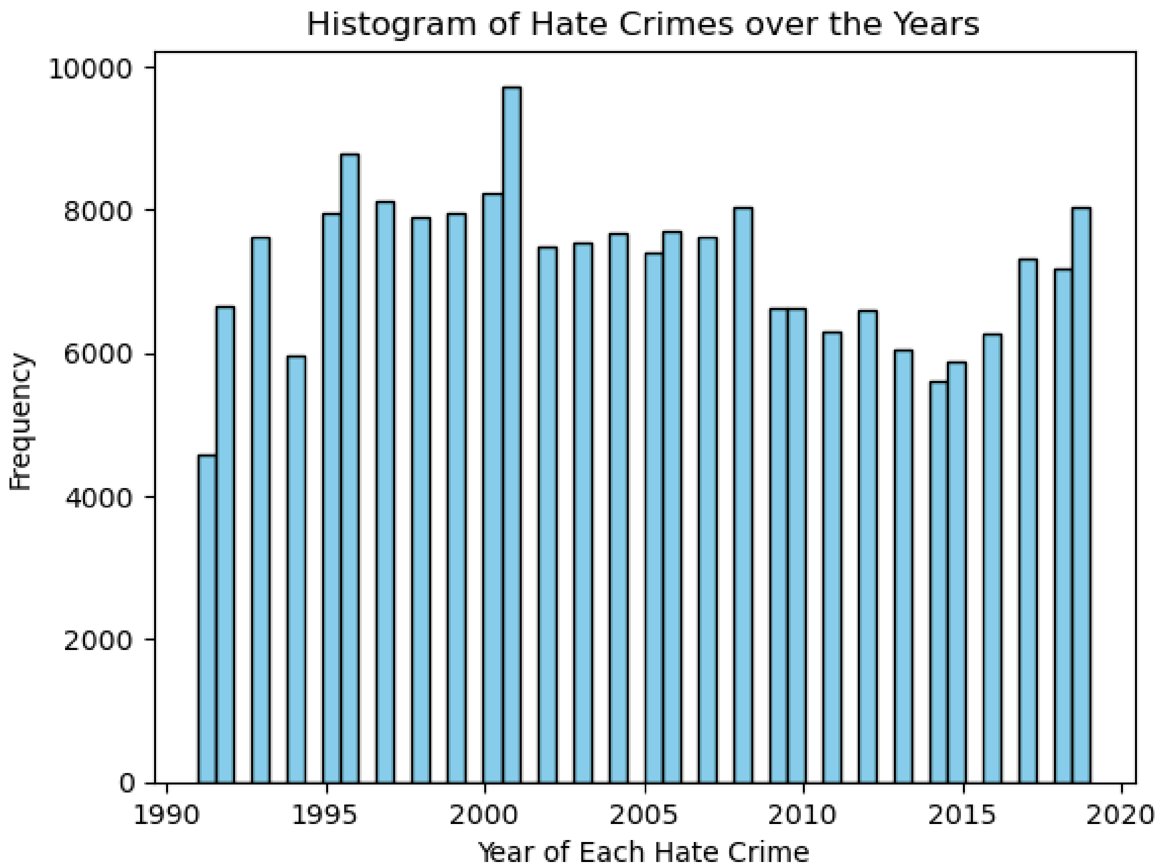
In terms of bias description, in other words, what type of marginalized group was victimized by the hate crime,
the most common biases are anti black/african american and anti-white which is consistent with our back ground
research telling us that the most common motivation for hate crimes is race related.

In [22]:
```
#Percentage Pie Chart of Crime Rates in different bias descriptions
counts = hcrime['OFFENSE_NAME'].value_counts()
labels = hcrime.OFFENSE_NAME.unique()
counts.plot.pie(autopct='%1.1f%%', labels= labels, shadow=True)

plt.title('Percentage distribution of OFFENSE_NAME column')

plt.axis('equal')
plt.show()
```



Here we look at our target varaible OFFENSE_NAME which is the type of offense that was committed. The most common being some form of assult or intimidation (verbal assault).

In [23]:
```
#Histogram Plot

plt.hist(orig_data.DATA_YEAR, bins=50, color='skyblue', edgecolor='black')
plt.xlabel('Year of Each Hate Crime')
plt.ylabel('Frequency')
plt.title('Histogram of Hate Crimes over the Years')
plt.show()
```




```
This last visual is just to show us how the rate of hate crimes has o
r hasn't been changing over the years. As you
can see from the distogram above, it's clear that since around 2015,
the amount of hate crimes committed in the
country has been increasing rather steadily, consistent with our prio
r findings as well. Now let's move onto our models.
```

Methods

```
The target variable that we are going to be concerned with is the off
ense name (OFFENSE_NAME) for the hate crime. It’s
also worth noting that since we’re going to be working with demograph
ic information, we might need to bring other data
into the mix (possibly looking at race proportions of each state) to
possibly determine whether demographic information
of a state can also shine like as to what hate crimes are most likely
and provide information as to what states are and
aren’t safe for specific marginalized groups of people. But once we h
ave our desired data and predicting variables we
will likely use logistic regression since our target variable is a ca
tegorical variable.

The first step in our analysis is variable selection, specifically ch
oosing which varaibles we will be using as our
predicting varables. In the end we chose to to drop the following var
aibles:

DATA_YEAR, TOTAL_OFFENDER_COUNT, VICTIM_COUNT, OFFENSE_NAME, and MULT
IPLE_OFFENSE.

We drop the year of the indicent because we are not concerned with kn
owing the year. In the end we want to predict what
type of hate crime will be commited based on factors such as demogrpa
hic infomration. We drop the total offender count
varaible because we are not concerned with how many offenders there w
e during an indicent, only whether or not that
incident occured and what happened. We drop the victim count because
again we are only concerned with what happened, not
```

Analysis and Model Creation

In [24]:
```
#Variable selection
X_vars = hcrime.drop(['DATA_YEAR', 'TOTAL_OFFENDER_COUNT', 'VICTIM_COUNT', 'OF
X_vars
```

Out[24]:

	STATE_ABBR	REGION_NAME	POPULATION_GROUP_DESC	OFFENDER_RACE	
0	AR	South	Cities from 10,000 thru 24,999	White	Highway/
1	AR	South	Cities from 2,500 thru 9,999	Black or African American	Highway/
2	AR	South	Cities from 50,000 thru 99,999	Black or African American	
3	AR	South	Cities from 50,000 thru 99,999	Black or African American	Highway/
4	AR	South	Cities from 50,000 thru 99,999	Black or African American	
...	...	...	...	...	
209437	WY	West	Cities from 25,000 thru 49,999	Unknown	(
209438	WY	West	Cities under 2,500	Multiple	
209439	WY	West	Cities from 2,500 thru 9,999	American Indian or Alaska Native	
209440	WY	West	Cities from 10,000 thru 24,999	American Indian or Alaska Native	
209441	WY	West	Cities from 10,000 thru 24,999	Black or African American	

165999 rows × 7 columns

After we have our desired predicting varaibles, since they are all categorical varaibles, we want to transform that datasent into dummy varaibles in order to be able to use that data to train our future model. After which we are able to get started with our model building process.

In [25]:
```
#change varaibles to dummy varaibles
X = pd.get_dummies(X_vars)
dummy_vars = X
X
```

Out[25]:

	STATE_ABBR_AK	STATE_ABBR_AL	STATE_ABBR_AR	STATE_ABBR_AZ	STATE_ABBR_
0	False	False	True	False	Fa
1	False	False	True	False	Fa
2	False	False	True	False	Fa
3	False	False	True	False	Fa
4	False	False	True	False	Fa
...	...	...	...	...	
209437	False	False	False	False	Fa
209438	False	False	False	False	Fa
209439	False	False	False	False	Fa
209440	False	False	False	False	Fa
209441	False	False	False	False	Fa

165999 rows × 193 columns

```
The first type of model that we try to create is a decision tree clas
sifier. Since we are predicting a cateogricical
varaible with more than two cateogories, we are not able to use logis
tic regression for our model. Decision tree models
are also ideal when you have a lot or all cateogorical predicting var
aibles as well. With this model we get an accuracy
of about 47.6% in our predictions.
```

In [26]:
```
#Splitting Training and Testing Sets and building Model

from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics

#split dataset in features and target variable
X =  X # Features
y = hcrime.OFFENSE_NAME # Target variable

# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.05, rand

# Create Decision Tree classifer object
clf = DecisionTreeClassifier()

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)
```

In [27]:
```
# Model Accuracy:
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.47771084337349395
```

```
Since we always want to strive for better accruacy, we next try a dif
ferent model. A random forrest instead of a
singular decision tree. Here we get an accruacy of about 50% which is
slightly better than our last model. We also
create a confusion matrix to show our results visually.
```

In [28]:
```
#Better Model Plan: Random Forest
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, precision_score,
from sklearn.model_selection import RandomizedSearchCV, train_test_split
from scipy.stats import randint

rf = RandomForestClassifier()
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
```

In [29]:
```
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.5067469879518073
```

Results

In [1]:
```
#creating confusion matrix

cm = metrics.confusion_matrix(y_test, y_pred)
cmp = ConfusionMatrixDisplay(cm)
fig, ax = plt.subplots(figsize=(10,8))
cmp.plot(ax=ax)

labels = hcrime['OFFENSE_NAME'].unique()
labels = pd.DataFrame(labels)
labels
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[1], line 3
      1 #creating confusion matrix
----> 3 cm = metrics.confusion_matrix(y_test, y_pred)
      4 cmp = ConfusionMatrixDisplay(cm)
      5 fig, ax = plt.subplots(figsize=(10,8))

NameError: name 'metrics' is not defined
```

Conclusion

```
Overall there were 33 different types of offenses possible so to be a
ble to predict the type of offence at just above
50% accuracy with our model does seem better than not being able to m
ake any type of guess. With our model, we are able
to predict the type of hate crime committed knowing the state the pos
sible victim lives in, the region of the country,
size of the population of the city, the race of possible offender, th
e location of the possible victim, the minority
group the possible victim belongs to and whether the victim is an ind
ividual or group of people (whether they are safer
in numbers or not).
```

```
# Assumptions:

    In order to make any conclusions, we assume that this sample data can
represent the whole of the united states and
    that there is sufficent data from each state and region to make valid
conclusions of our findings. As far as any model
    assumptions, decision trees/random forests are a non-parametric, non-
statistical method that doesn't make assumptions
    about the distribution, independence, or constant variance of training
data or prediction residuals. They also don't
```

```
assume linearity in the data.
```

Limitations:

```
As far as limiations went, I think while this is the most data we hav
e worked with as far as projects, there could have
been more data to fit our original plan. Originally, we only wanted t
o be concerned with hate crimes committed towards
individals, but getting rid of other victim types could have gotten r
id of a few thousand observations so we decided to
keep all victim types and open that analysis. More data is always goo
d in analysis. We are also limited by the dark
figure of crime, all the crimes that haven't been reported due to pre
judice (for example, some people might be hesitant
to report rapes, or LGBT related crimes out of the fear of being expo
sed somehow). There is a lot to consider in that
aspect.
```

Challenges:

```
The main challenge I can see at this point is the vast amount of data
(clearly in the tens of thousands in terms of
the dataset I currently what to use). With that comes a lot of challe
nges in regards to even just cleaning and
formatting the data.
```

Future Uses/Additional Applications:

```
The aim of this investigation is to be able to use this model in orde
r to predict whether an individual (or any other
victim type in this case) based on the state they are in, region of t
he country, population size of location, the race
of possible offender (included as a demographic marker), type of loca
```

Ethical Assessment

```
As for ethical concerns, this is a pretty heavy topic having to do wi
th actual victims. It can be a very traumatic
experience so it’s important to remember that this data represents ac
tual events that happened to actual people. No
names are included in the data but there is plenty of personal inform
ation included so the data should be treated
with caution as always. Another thing to remember is that the finding
s of the investigation should be treated with
skepticism as well as crime in general tends to have a hidden figure.
Not all crimes are reported and documented
hence we can’t treat the data set as all the data of the population,
only a representation.
```

References

2022 FBI hate crimes statistics. Community Relations Service. (2023, October 30). https://www.justice.gov/crs/highlights/2022-hate-crime-statistics (https://www.justice.gov/crs/highlights/2022-hate-crime-statistics)

Jonathan. (2021, December 9). FBI hate crimes in USA (1991-2020). Kaggle. https://www.kaggle.com/datasets/jonathanrevere/fbi-hate-crimes-in-usa-19912020?select=Hate%2BCrimes%2Bin%2BAK%2B1991-2020.csv (https://www.kaggle.com/datasets/jonathanrevere/fbi-hate-crimes-in-usa-19912020?select=Hate%2BCrimes%2Bin%2BAK%2B1991-2020.csv)

Sai, P. (2023, March 13). Hate_crime_usa. Kaggle. https://www.kaggle.com/datasets/pavansb/hate-crime-usa (https://www.kaggle.com/datasets/pavansb/hate-crime-usa)

Appendix

Table 1: Original Dataframe

In [31]:
```
orig_data
```

Out[31]:

	INCIDENT_ID	DATA_YEAR	ORI	PUB_AGENCY_NAME	PUB_AGENCY_UNIT	AGE
0	3015	1991	AR0040200	Rogers	NaN	
1	3016	1991	AR0290100	Hope	NaN	
2	43	1991	AR0350100	Pine Bluff	NaN	
3	44	1991	AR0350100	Pine Bluff	NaN	
4	3017	1991	AR0350100	Pine Bluff	NaN	
...	...	...	...	...	...	
209437	558879	2019	WY0010100	Laramie	NaN	
209438	558880	2019	WY0010200	University of Wyoming	NaN	U
209439	661208	2019	WY0150100	Cody	NaN	
209440	463806	2019	WY0170100	Sheridan	NaN	
209441	705012	2019	WY0210100	Evanston	NaN	

209442 rows × 28 columns

Table 2: Dummy Variable transformation

In [32]:
```
dummy_vars
```

Out[32]:

	STATE_ABBR_AK	STATE_ABBR_AL	STATE_ABBR_AR	STATE_ABBR_AZ	STATE_ABBR_
0	False	False	True	False	Fa
1	False	False	True	False	Fa
2	False	False	True	False	Fa
3	False	False	True	False	Fa
4	False	False	True	False	Fa
...	...	...	...	...	
209437	False	False	False	False	Fa
209438	False	False	False	False	Fa
209439	False	False	False	False	Fa
209440	False	False	False	False	Fa
209441	False	False	False	False	Fa

165999 rows × 193 columns

Figure 1: Pie Chart of States

In [33]:
```
#Percentage Pie Chart of Crime Rates in different States
orig_data['STATE_ABBR'].value_counts()
counts = orig_data['STATE_ABBR'].value_counts()
labels = orig_data.STATE_ABBR.unique()
counts.plot.pie(autopct='%1.1f%%', labels= labels, shadow=True)

plt.title('Percentage distribution of STATE_ABBR column')

plt.axis('equal')
plt.show()
```

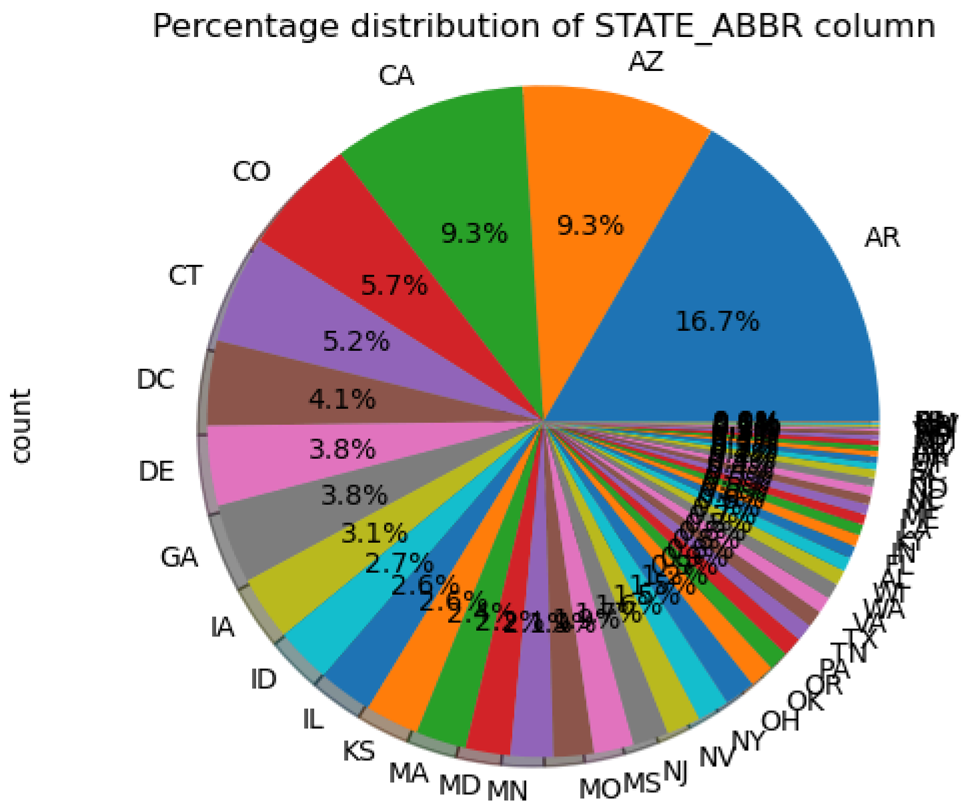


Figure 2: Pie Chart of Population Group Size

In [34]:
```python
#Percentage Pie Chart of Crime Rates in different Population Sizes
counts = orig_data['POPULATION_GROUP_DESC'].value_counts()
labels = orig_data.POPULATION_GROUP_DESC.unique()
counts.plot.pie(autopct='%1.1f%%', labels= labels, shadow=True)

plt.title('Percentage distribution of POPULATION_GROUP_DESC column')

plt.axis('equal')
plt.show()
```

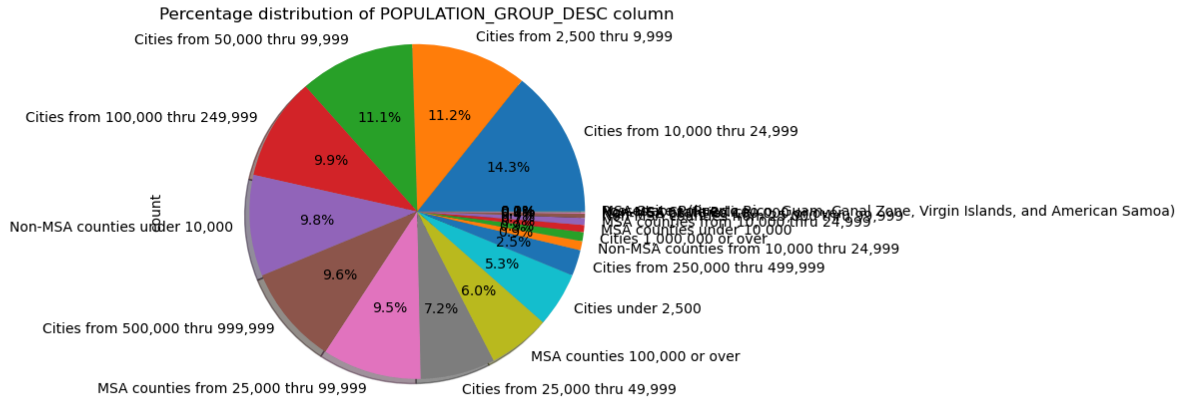


Figure 3: Pie Chart of Country Region Name

In [35]:
```
#Percentage Pie Chart of Crime Rates in different Regions
counts = orig_data['REGION_NAME'].value_counts()
labels = orig_data.REGION_NAME.unique()
counts.plot.pie(autopct='%1.1f%%', labels= labels, shadow=True)

plt.title('Percentage distribution of REGION_NAME column')

plt.axis('equal')
plt.show()
```

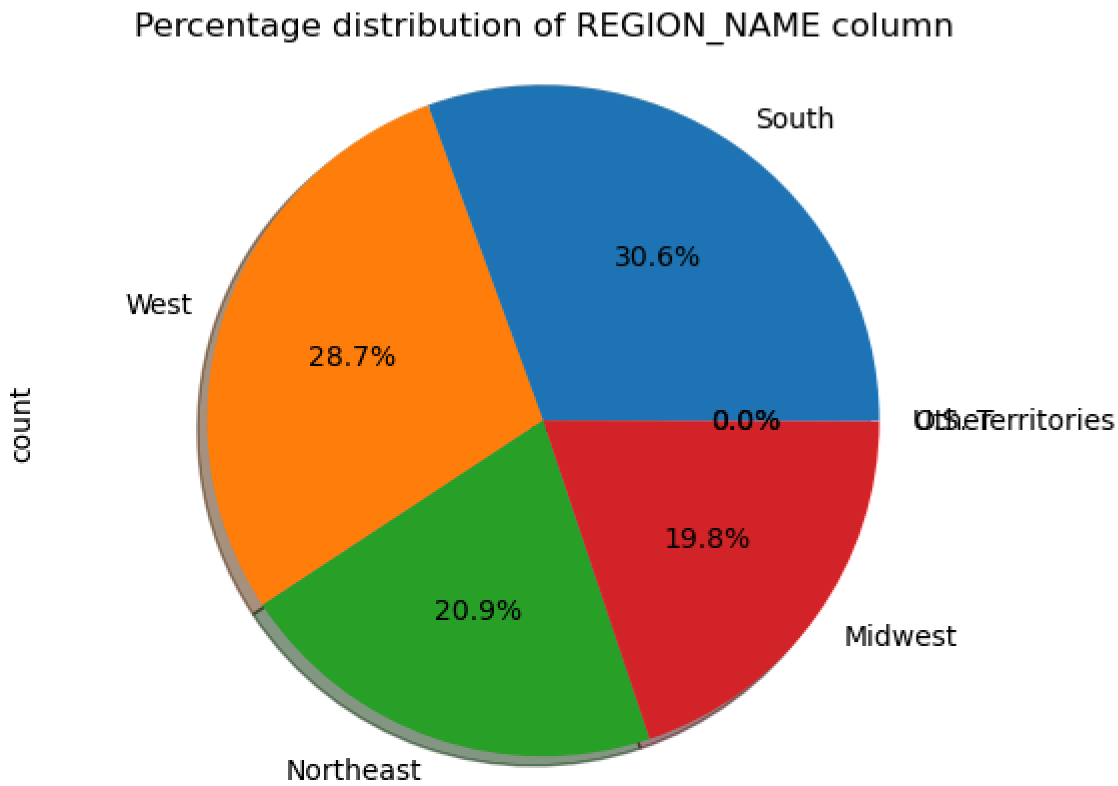
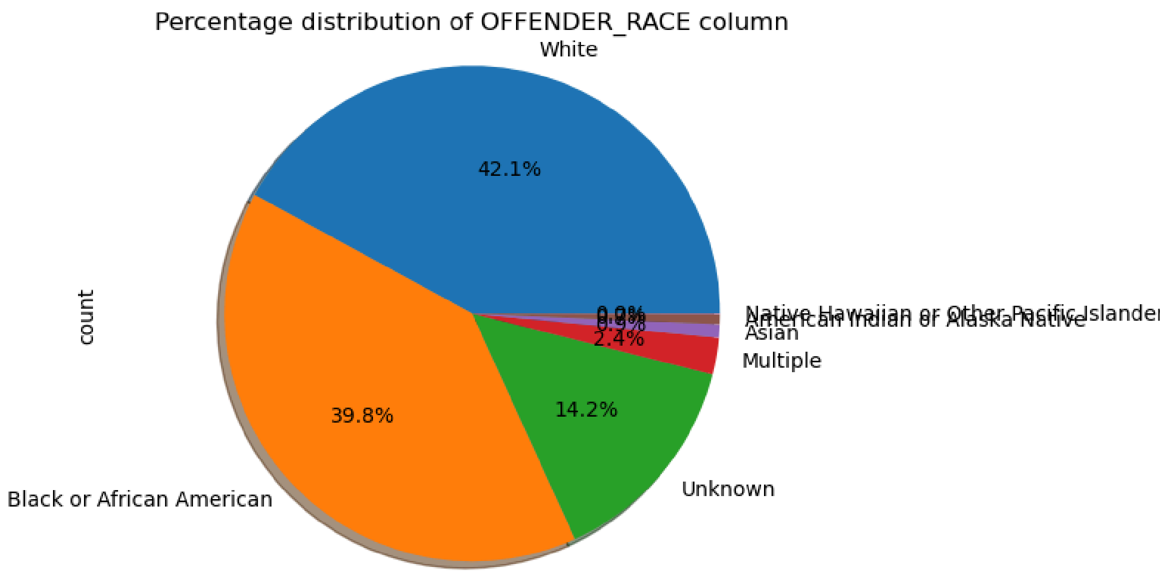


Figure 4: Pie Chart of Offender Race

In [36]:
```
#Percentage Pie Chart of Crime Rates in different races
counts = hcrime['OFFENDER_RACE'].value_counts()
labels = hcrime.OFFENDER_RACE.unique()
counts.plot.pie(autopct='%1.1f%%', labels= labels, shadow=True)

plt.title('Percentage distribution of OFFENDER_RACE column')

plt.axis('equal')
plt.show()
```



Audience Questions:

1. What was the main reason you chose this topic for your investigation?

   As I mentioned in the introduction to this project, hate crimes have both a social and political element to them. While they can be politically motivated, they are a reflection of our society regardless. Regardless of how you feel about yourself, other people will judge you whether you are part of any of those bias groups and it's important to know where you are safe in this country. That was the whole reason of this investigation.
2. Do you believe the data was adequate enough for your investigation and chosen research question?

   I believe that there was certainly enough data in the data set we found. There was enough and the right type of data to complete this project but I do think that different TYPES of data could have been helpful for the investigation. For example it would have been nice if the dataset included more balanced cateogories for cateogrical varaibles. It was clear that the data we worked with was somewhat "raw". It would have also been nice to have more demographic information about the location, city and state the incidents occured in to have a better profile for each location.
3. Would you have chosen a different question given the time and resources?

   I don't think I would have. I felt really passionate about this research topic and I do think that I executed it the way I wanted to and planned to for the most part.

4. If you had more time, what would you further investigate?

   I would definitely dive into more demographic information for each state, possibly create some kind of profile for each location as well. Perhaps looking into different races/ethnicities and their distribution in each state, looking at the regular crime rate in each state as well for reference, and things of that nature.
5. What ethical concerns did you need to consider?

   We need to be considerate that the data might not reflect the population as a whole. Each observations are considered willing participants. Each incident was reported. There are no crimes/indidents that no one had reported. We also acknowledge the sensitivity of the data. This is a serious topic in which real lives were impacted. Some of these incident reports can lead to serious trauma for the victims and it's important to appraoch with respect.
6. Was the large amount of data a problem or limiting factor in your investigation?

   It didn't feel like a problem. If anything it was an advantage to work with so much data because we were then able to narrow down the exact data we wanted to work with without sacrificing our sample size. In the end, after getting rid of a good amount of columns and rows, we still had sufficient data to work with and create our model.
7. If you could do anything differently about this project, what would it be and why?

   I honestly wouldn't change much about this project but if I could I would want to maybe expand the investigation to more areas of the world, not just the United States. But such an investigation would be difficult considering there are different procedures of reporting crimes and other conditions which are different country to country. It would be inconsident data collection.
8. What sort of application do you think your findings may have for society?

   Our findings can serve as a sort of guidelines for the safety of different marginilized victims.
9. What was your favorite part of the analysis?

   My favorite part was honestly creating the models and being able to create a confusion matrix of our results. I had never really worked with a confusion matrix larger than 2x2 so it was interesting to look at those results as well. It's always nice to be able to get some sort of visual of your results, not just looking at the accruacy numbers. You can then see the areas the model excelled and did poorly on.
10. What do you have to say as far as data accuracy for this investigation topic?

    I would say that the fact that these incidents were observations recorded by the FBI itself, I would hand the data a good amount of credibility. As far as accuracy goes in terms of representing the population as a whole, it might not be as credible considering that not all crimes are always reported nor are they always reported accurately. People cna forget what happens. Some crimes aren't even reported as soon as they happen.