capstone_project_cleanup_EDA

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Modeling and Forecasting Crime Rate in Colorado

Data Science Capstone Project, part 2; (pre-processing DataFrames and EDA) * Student name: Elena Kazakova * Student pace: Full-time * Cohort: DS02222021 * Scheduled project review date: 07/26/2021 * Instructor name: James Irving * Application url: TBD

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1 OBTAIN

If you are running this notebook without restarting the kernel replace '%load_ext autoreload' in imports with '%reload_ext autoreload'

1.1 Imports

[1]:
```
# Importing packages
import pandas as pd
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import itertools
import statsmodels
import statsmodels.tsa.api as tsa
import plotly.express as px
import plotly.io as pio
import plotly
import math
from math import sqrt
import holidays
import pmdarima as pm

from statsmodels.tsa.stattools import adfuller, acf, pacf
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.statespace.sarimax import SARIMAX
from sklearn.metrics import mean_squared_error

import pickle
#import shutil
import os
import json

# from pathlib import Path
# import subprocess
# import io

import warnings
warnings.filterwarnings(action='ignore', category=FutureWarning)

from functions_all import *

%reload_ext autoreload
%autoreload 2
%matplotlib inline
```

[2]:
```
CO_zip_json=json.load(open('data/co_zip.min.json', 'r'))
CO_county_json=json.load(open('data/CO_counties_geo.json', 'r'))
```

1.2 Data

1.2.1 Data source and data description

Data is from FBI Crime Data Explorer NIBRS data for Colorado from 2009-2019

The data dictionary is and a record descriptiopn are available.

The description of the main and reference tables is in data/README.md file. The FBI implemented some changes to the files structure in 2016 and removed the sqlite create and load scripts from the zip directories. Another fact worth mentioning is that files 'nibrs_property_desc.csv' from 2014 and 2015 have duplicated nibrs_property_desc_ids (unique identifier in the nibrs_property_desc table) which complicated the loading of the data.

1. The first part of the scrubbing process (working with sqlite3 database, production1) is in part I notebook. It takes about 12 minutes to run the code in this notebook. The following notebook is using dataframes created in part I.

2. Also the full original data description is in the same part I notebook.

3. The notebook with database creation is in the part ZERO notebook. The referenced database is in ***data/sqlite/db/production1***. It takes 2.5 minutes to run the database creation script.

2 SCRUB

2.1 Part I, pre-processing the data in SQL database

In part I the following dataframes have been created and saved in the pickle files:

```
1. df_incident: data/pickled_dataframes/incident.pickle; main incident DF with date/time of an
2. df_offense: data/pickled_dataframes/offense.pickle: main offense DF with offense names and
3. df_offender: data/pickled_dataframes/offender.pickle; main offender DF with demographic info
4. df_victim: data/pickled_dataframes/victim.pickle; main victim DF with demographic info
5. df_weapon: data/pickled_dataframes/weapon.pickle; main weapon DF with a weapon category used
6. df_bias: data/pickled_dataframes/bias.pickle; main bias DF with offense bias motivation
7. df_rel: data/pickled_dataframes/relationship.pickle; main victim-offender relationship DF wi
```

2.2 Part II, scrubbing the data in DataFrames

2.2.1 Using pickle files to create dataframes

[3]:
```
with open('data/pickled_dataframes/incident.pickle', 'rb') as f:
    df_incident=pickle.load(f)
df_incident.head()
```

[3]:

	agency_id	incident_id	incident_date	incident_hour	primary_county	\
0	1971	51264520	2009-01-05 00:00:00	22	Kit Carson	
1	1971	51264521	2009-01-13 00:00:00	25	Kit Carson	
2	1971	51264523	2009-01-17 00:00:00	19	Kit Carson	
3	1971	51264524	2009-01-20 00:00:00	25	Kit Carson	
4	1971	51264525	2009-01-21 00:00:00	25	Kit Carson	

```
  icpsr_zip
0     80807
1     80807
2     80807
3     80807
4     80807
```

[4]:
```
len(df_incident)
```

[4]:
```
2819463
```

[5]:
```
with open('data/pickled_dataframes/offense.pickle', 'rb') as f:
    df_offense=pickle.load(f)
df_offense.head()
```

[5]:
```
   offense_id  incident_id   location_name               offense_name  \
0    53563151     51264520  Residence/Home         Aggravated Assault
1    53563402     51264521  Residence/Home   Theft From Motor Vehicle
2    53558278     51264523  School/College   Drug/Narcotic Violations
3    53558279     51264523  School/College  Drug Equipment Violations
4    53563403     51264524   Other/Unknown              Impersonation

  crime_against   offense_category_name
0        Person         Assault Offenses
1      Property  Larceny/Theft Offenses
2       Society  Drug/Narcotic Offenses
3       Society  Drug/Narcotic Offenses
4      Property           Fraud Offenses
```

[6]:
```
len(df_offense)
```

[6]:
```
3201143
```

[7]:
```
with open('data/pickled_dataframes/offender.pickle', 'rb') as f:
    df_offender=pickle.load(f)
df_offender.head()
```

[7]:
```
   offender_id  incident_id age_num sex_code   race     age_group ethnicity
0     57702592     51264520      25     Male  White  Age in Years      None
1     57702593     51264521                    None          None      None
2     57702595     51264523      20     Male  White  Age in Years      None
3     57702596     51264524                    None          None      None
4     57702597     51264525      55     Male  White  Age in Years      None
```

[8]:
```
len(df_offender)
```

[8]:
```
3197991
```

[9]:
```
with open('data/pickled_dataframes/victim.pickle', 'rb') as f:
    df_victim=pickle.load(f)
df_victim.head()
```

[9]:

	victim_id	incident_id	age_num	sex_code	resident_status_code	race	age_group	ethnicity	victim_type
0	55514644	51264520	23	Male	Resident	White	Age in Years	Not Hispanic or Latino	Law Enforcement Officer
1	55514645	51264521	49	Female	Non-resident	White	Age in Years	Unknown	Individual
2	55514647	51264523				None	None	None	Society/Public
3	55514648	51264524	28	Female	Resident	White	Age in Years	Unknown	Individual
4	55514649	51264525	16	Male	Resident	White	Age in Years	Unknown	Individual

[10]:
```
len(df_victim)
```

[10]:
```
3229640
```

[11]:
```
with open('data/pickled_dataframes/weapon.pickle', 'rb') as f:
    df_weapon=pickle.load(f)
df_weapon.head()
```

[11]:

	offense_id	weapon
0	53563151	Non-automatic firearm
1	53558280	Non-automatic firearm
2	53563153	Non-automatic firearm
3	53579810	Non-automatic firearm
4	53572975	Non-automatic firearm

[12]:
```
len(df_weapon)
```

[12]:
```
551049
```

[13]:
```
with open('data/pickled_dataframes/bias.pickle', 'rb') as f:
    df_bias=pickle.load(f)
df_bias.head()
```

[13]:

	offense_id	bias_name
0	53563151	None
1	53563402	None
2	53558278	None
3	53558279	None
4	53563403	None

[14]:
```
len(df_bias)
```

[14]:
```
3201158
```

[15]:
```
with open('data/pickled_dataframes/relationship.pickle', 'rb') as f:
    df_rel=pickle.load(f)
df_rel.head()
```

[15]:
```
   victim_id  offender_id                relationship_name
0   55514644     57702592       Victim was Otherwise Known
1   55514649     57702597             Victim Was Stepchild
2   55514652     57702601                Victim Was Spouse
3   55514653     57702602  Victim Was Boyfriend/Girlfriend
4   55514655     57702604                 Victim Was Child
```

[16]:
```
len(df_rel)
```

[16]:
```
794157
```

The next step is scrubbing the dataframes

2.2.2 Checking for duplicates, missing values and other abnormalities, incident table

[17]:
```
df_incident.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2819463 entries, 0 to 2819462
Data columns (total 6 columns):
 #   Column          Dtype
---  ------          -----
 0   agency_id       int64
 1   incident_id     int64
 2   incident_date   object
 3   incident_hour   int64
 4   primary_county  object
 5   icpsr_zip       object
dtypes: int64(3), object(3)
memory usage: 129.1+ MB
```

Converting incident_date column to a datetime type

[18]:
```
df_incident.head()
```

[18]:
```
   agency_id  incident_id        incident_date  incident_hour primary_county  \
0       1971     51264520  2009-01-05 00:00:00             22     Kit Carson
1       1971     51264521  2009-01-13 00:00:00             25     Kit Carson
2       1971     51264523  2009-01-17 00:00:00             19     Kit Carson
3       1971     51264524  2009-01-20 00:00:00             25     Kit Carson
4       1971     51264525  2009-01-21 00:00:00             25     Kit Carson
```

```
  icpsr_zip
0     80807
1     80807
2     80807
3     80807
4     80807
```

[19]:
```
df_incident['timestamp']=pd.to_datetime(df_incident.incident_date)
df_incident.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2819463 entries, 0 to 2819462
Data columns (total 7 columns):
 #   Column          Dtype
---  ------          -----
 0   agency_id       int64
 1   incident_id     int64
 2   incident_date   object
 3   incident_hour   int64
 4   primary_county  object
 5   icpsr_zip       object
 6   timestamp       datetime64[ns]
dtypes: datetime64[ns](1), int64(3), object(3)
memory usage: 150.6+ MB
```

[20]:
```
df_incident.sort_values('timestamp', ascending=True)
```

[20]:

	agency_id	incident_id	incident_date	incident_hour	\
40230	1984	51269326	2009-01-01 00:00:00	12	
184495	2119	47560373	2009-01-01 00:00:00	1	
184494	2119	47560372	2009-01-01 00:00:00	22	
109516	1831	49921447	2009-01-01 00:00:00	10	
109514	1831	49942735	2009-01-01 00:00:00	25	
…	…	…	…	…	
2685274	2119	122863693	31-Dec-19	16	
2807672	2010	119343129	31-Dec-19	21	
2719556	1920	120335390	31-Dec-19	21	
2583020	2051	120330349	31-Dec-19	23	
2686115	2119	122863605	31-Dec-19	15	

	primary_county	icpsr_zip	timestamp
40230	Larimer	80525	2009-01-01
184495	Denver	80204	2009-01-01
184494	Denver	80204	2009-01-01
109516	Adams	80031	2009-01-01
109514	Adams	80031	2009-01-01
…	…	…	…

```
2685274         Denver     80204 2019-12-31
2807672         Moffat     81625 2019-12-31
2719556        El Paso     80901 2019-12-31
2583020         Pueblo     81003 2019-12-31
2686115         Denver     80204 2019-12-31

[2819463 rows x 7 columns]
```

Checking for duplicates and dropping them

[21]:
```
df=df_incident[df_incident.duplicated(subset=['incident_id'],keep=False)].
 ↪sort_values(by=['incident_id','timestamp'])
df
```

[21]:
```
          agency_id  incident_id        incident_date  incident_hour  \
1456847        1908     85757101  2015-08-10 00:00:00             17
1733099        1908     85757101            20-Jan-16             22
1456848        1908     85757105  2015-08-10 00:00:00             17
1733102        1908     85757105            19-Jan-16             10
1456849        1908     85757108  2015-08-10 00:00:00             17
…               …           …                   …              …
1889452        1920     88326562             1-Nov-16             14
1448247        1893     88338695  2015-05-06 00:00:00             15
1830888        1827     88338695            31-Jul-16              7
1448388        1893     88339624  2015-12-09 00:00:00             14
1830718        1827     88339624             6-Oct-16             13

         primary_county icpsr_zip  timestamp
1456847         Douglas     80124 2015-08-10
1733099         Douglas     80124 2016-01-20
1456848         Douglas     80124 2015-08-10
1733102         Douglas     80124 2016-01-19
1456849         Douglas     80124 2015-08-10
…                 …         …          …
1889452         El Paso     80901 2016-11-01
1448247           Delta     81416 2015-05-06
1830888        Arapahoe     80012 2016-07-31
1448388           Delta     81416 2015-12-09
1830718        Arapahoe     80012 2016-10-06

[548 rows x 7 columns]
```

There are 548 duplicate incident_id, they seem to be from different dates, counties, zipcodes. Only the first duplicate will be left in the set. The presence of duplicate incident_ids is most probably a human error when the system got switched to another format in 2016.

[22]:
```
# Dropping rows with duplicate ids and 2016 timestamp (becase their indices are␣
↪higher). Removing 'incident_date' column.

df_incident=df_incident.drop_duplicates(subset=['incident_id'],keep='last')
```

[23]:
```
df_incident=df_incident.drop(columns=['incident_date'])
df_incident.head()
```

[23]:

	agency_id	incident_id	incident_hour	primary_county	icpsr_zip	timestamp
0	1971	51264520	22	Kit Carson	80807	2009-01-05
1	1971	51264521	25	Kit Carson	80807	2009-01-13
2	1971	51264523	19	Kit Carson	80807	2009-01-17
3	1971	51264524	25	Kit Carson	80807	2009-01-20
4	1971	51264525	25	Kit Carson	80807	2009-01-21

Checking for empty strings/null values and updating the rows with new values

[24]:
```
# Cheching for empty strings and null values
empty_string_count(df_incident)
```

```
Column agency_id empty string count: 0
Column agency_id null values count: 0
**************************************************
Column incident_id empty string count: 0
Column incident_id null values count: 0
**************************************************
Column incident_hour empty string count: 0
Column incident_hour null values count: 0
**************************************************
Column primary_county empty string count: 13771
Column primary_county null values count: 0
**************************************************
Column icpsr_zip empty string count: 2277
Column icpsr_zip null values count: 0
**************************************************
Column timestamp empty string count: 0
Column timestamp null values count: 0
**************************************************
Total number of records in the dataframe: 2819189
```

There are no NaN values but ''(empty string) values are present in primary_county and icpsr_zipcode fields

[25]:
```
df=df_incident.loc[df_incident['primary_county']=='']
df.icpsr_zip.unique()
```

[25]:
```
array(['80215'], dtype=object)
```

Due to the fact that all primary_county missing values are associated with 80215 zip code, which belongs to Jefferson county. I am filling in these records primary county with 'Jefferson' string.

[26]:
```
df_incident.loc[df_incident.primary_county == '', 'primary_county'] =␣
↪'Jefferson'
```

[27]:
```
df=df_incident.loc[df_incident['icpsr_zip']=='']
df.agency_id.unique()
```

[27]:
```
array([ 1982, 23131, 25314], dtype=int64)
```

The missing zip codes belong to the following agencies: 1. agency_id=1982: Fort Lewis College, located in 81301 zip code 2. agency_id=23131: South Metro Drug Task Force, located in 80160 zip code 3. agency_id=25314: Gypsum Police Department, located in 81637 zip code

The values above will be used to fill in icpsr_zip column values in place of '' values

[28]:
```
df_incident.loc[((df_incident.icpsr_zip == '')&(df_incident.agency_id==1982)),␣
↪'icpsr_zip'] = '81301'

df_incident.loc[((df_incident.icpsr_zip == '')&(df_incident.agency_id==23131)),␣
↪'icpsr_zip'] = '80160'

df_incident.loc[((df_incident.icpsr_zip == '')&(df_incident.agency_id==25314)),␣
↪'icpsr_zip'] = '81637'
```

[29]:
```
empty_string_count(df_incident)
```

```
Column agency_id empty string count: 0
Column agency_id null values count: 0
**************************************************
Column incident_id empty string count: 0
Column incident_id null values count: 0
**************************************************
Column incident_hour empty string count: 0
Column incident_hour null values count: 0
**************************************************
Column primary_county empty string count: 0
Column primary_county null values count: 0
**************************************************
Column icpsr_zip empty string count: 0
Column icpsr_zip null values count: 0
**************************************************
Column timestamp empty string count: 0
Column timestamp null values count: 0
**************************************************
Total number of records in the dataframe: 2819189
```

2.2.3 Checking for duplicates, missing values and other abnormalities, offense table

[30]:
```
df_offense.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3201143 entries, 0 to 3201142
Data columns (total 6 columns):
 #   Column                Dtype
---  ------                -----
 0   offense_id            int64
 1   incident_id           int64
 2   location_name         object
 3   offense_name          object
 4   crime_against         object
 5   offense_category_name  object
dtypes: int64(2), object(4)
memory usage: 146.5+ MB
```

[31]:
```
df_offense.head()
```

[31]:

	offense_id	incident_id	location_name	offense_name	crime_against	offense_category_name
0	53563151	51264520	Residence/Home	Aggravated Assault	Person	Assault Offenses
1	53563402	51264521	Residence/Home	Theft From Motor Vehicle	Property	Larceny/Theft Offenses
2	53558278	51264523	School/College	Drug/Narcotic Violations	Society	Drug/Narcotic Offenses
3	53558279	51264523	School/College	Drug Equipment Violations	Society	Drug/Narcotic Offenses
4	53563403	51264524	Other/Unknown	Impersonation	Property	Fraud Offenses

Checking for duplicates

[32]:
```
df=df_offense[df_offense.duplicated(subset=['offense_id'],keep=False)].
↪sort_values(by='offense_id')
df
```

[32]:
```
Empty DataFrame
Columns: [offense_id, incident_id, location_name, offense_name, crime_against,
offense_category_name]
Index: []
```

There are no duplicate offense_ids

Checking for empty strings/null values and updating the rows with new values

[33]:
```
empty_string_count(df_offense)
```

```
Column offense_id empty string count: 0
Column offense_id null values count: 0
**************************************************
Column incident_id empty string count: 0
Column incident_id null values count: 0
**************************************************
Column location_name empty string count: 0
Column location_name null values count: 0
**************************************************
Column offense_name empty string count: 0
Column offense_name null values count: 0
**************************************************
Column crime_against empty string count: 0
Column crime_against null values count: 0
**************************************************
Column offense_category_name empty string count: 0
Column offense_category_name null values count: 0
**************************************************
Total number of records in the dataframe: 3201143
```

There are no rows with empty strings or NaN values

2.2.4 Checking for duplicates, missing values and other abnormalities, victim table

[34]:
```
df_victim.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3229640 entries, 0 to 3229639
Data columns (total 9 columns):
 #   Column                Dtype
---  ------                -----
 0   victim_id             int64
 1   incident_id           int64
 2   age_num               object
 3   sex_code              object
 4   resident_status_code  object
 5   race                  object
 6   age_group             object
 7   ethnicity             object
 8   victim_type           object
dtypes: int64(2), object(7)
memory usage: 221.8+ MB
```

[35]:
```
df_victim.head()
```

[35]:

	victim_id	incident_id	age_num	sex_code	resident_status_code	race	\
0	55514644	51264520	23	Male	Resident	White	
1	55514645	51264521	49	Female	Non-resident	White	

```
2   55514647     51264523                                        None
3   55514648     51264524      28   Female             Resident  White
4   55514649     51264525      16     Male             Resident  White

      age_group               ethnicity              victim_type
0  Age in Years  Not Hispanic or Latino  Law Enforcement Officer
1  Age in Years                 Unknown               Individual
2          None                    None          Society/Public
3  Age in Years                 Unknown               Individual
4  Age in Years                 Unknown               Individual
```

Checking for duplicates **The same person can be a victim in several incidents therefore we are only checking for duplicates with victim_ids AND incident_ids**

[36]:
```
df=df_victim[df_victim.
 ↪duplicated(subset=['victim_id','incident_id'],keep=False)].
 ↪sort_values(by='victim_id')
df
```

[36]:
```
Empty DataFrame
Columns: [victim_id, incident_id, age_num, sex_code, resident_status_code, race,
age_group, ethnicity, victim_type]
Index: []
```

No duplicates found

Checking for empty strings/null values

[37]:
```
empty_string_count(df_victim)
```

```
Column victim_id empty string count: 0
Column victim_id null values count: 0
**************************************************
Column incident_id empty string count: 0
Column incident_id null values count: 0
**************************************************
Column age_num empty string count: 1032415
Column age_num null values count: 0
**************************************************
Column sex_code empty string count: 991009
Column sex_code null values count: 0
**************************************************
Column resident_status_code empty string count: 1068153
Column resident_status_code null values count: 0
**************************************************
Column race empty string count: 0
Column race null values count: 991009
**************************************************
Column age_group empty string count: 0
```

```
Column age_group null values count: 991009
**************************************************
Column ethnicity empty string count: 0
Column ethnicity null values count: 1013219
**************************************************
Column victim_type empty string count: 0
Column victim_type null values count: 0
**************************************************
Total number of records in the dataframe: 3229640
```

Abnormal values, victim table

race, NaN values

[38]:
```
df=df_victim[df_victim.race.isnull()]
df.victim_type.unique()
```

[38]:
```
array(['Society/Public', 'Business', 'Government', 'Other', 'Unknown',
       'Financial Institution', 'Religious Organization'], dtype=object)
```

The NAN values in the race column of victims with of types **'Society/Public', 'Business', 'Government', 'Other','Unknown', 'Financial Institution', and 'Religious Organization'** will be replaced with **'NA'** value. Due to the fact that these victim types are the only types of NULL race records, all race NULL values will replaced with 'NA'.

[39]:
```
df_victim.loc[df_victim.race.isnull(), 'race'] = 'NA'
```

ethnicity, NaN values

[40]:
```
df=df_victim[df_victim.ethnicity.isnull()]
df.victim_type.unique()
```

[40]:
```
array(['Society/Public', 'Individual', 'Business', 'Government', 'Other',
       'Unknown', 'Financial Institution', 'Religious Organization',
       'Law Enforcement Officer'], dtype=object)
```

[41]:
```
df=df_victim[((df_victim.ethnicity.isnull()) & (df.victim_type.isin(['Law␣
 ↪Enforcement Officer', 'Individual'])))]
print('Number of records with empty string in resident_status_code and␣
 ↪Individual or \
Law Inforcement victim type: {}'.format(len(df)))
df.head()
```

```
Number of records with empty string in resident_status_code and Individual or
Law Inforcement victim type: 22210
```

[41]:

	victim_id	incident_id	age_num	sex_code	resident_status_code	\
7	55514663	51264539	65	Male	Resident	
37	55514681	51264550	24	Male	Resident	
55	55514698	51264566	29	Female	Resident	

```
116     54355540     50210712      39   Female             Resident
13355   54431861     50279345      43     Male             Resident

                             race     age_group ethnicity victim_type
7                           White  Age in Years      None  Individual
37                          White  Age in Years      None  Individual
55                          White  Age in Years      None  Individual
116                         White  Age in Years      None  Individual
13355  Black or African American  Age in Years      None  Individual
```

1. The NaN values in the ethnicity column of victims with of types **'Society/Public', 'Business', 'Government', 'Other','Unknown', Financial Institution', and 'Religious Organization'** will be replaced with **'NA'** value 2. The NaN values in the ethnicity column of victims with of types **'Law Enforcement Officer', 'Individual'** will be replaced with **'Unknown'** value

[42]:
```
df_victim.loc[(df_victim.ethnicity.isnull()
               &df_victim.victim_type.isin(['Society/Public','Business',␣
 ↪'Government','Other','Unknown',
                                            'Financial Institution','Religious␣
 ↪Organization'])), 'ethnicity'] = 'NA'

df_victim.loc[(df_victim.ethnicity.isnull()
               &df_victim.victim_type.isin(['Law Enforcement Officer',␣
 ↪'Individual'])), 'ethnicity'] = 'Unknown'
```

age_group, NaN values

[43]:
```
df=df_victim[df_victim.age_group.isnull()]
df.victim_type.unique()
```

[43]:
```
array(['Society/Public', 'Business', 'Government', 'Other', 'Unknown',
       'Financial Institution', 'Religious Organization'], dtype=object)
```

The NAN values in the age_group column of victims with of types **'Society/Public', 'Business', 'Government', 'Other','Unknown', 'Financial Institution', and 'Religious Organization'** will be replaced with **'NA'** value. Due to the fact that these victim types are the only types of NULL age_group records, all age_group NULL will replaced with 'NA'.

[44]:
```
df_victim.loc[df_victim.age_group.isnull(), 'age_group'] = 'NA'
```

age_num, empty string values

[45]:
```
df=df_victim[df_victim.age_num=='']
print('Number of records with empty string in age_num: {}'.format(len(df)))
df.victim_type.unique()
```

```
Number of records with empty string in age_num: 1032415
```

[45]:
```
array(['Society/Public', 'Business', 'Government', 'Other',
       'Law Enforcement Officer', 'Individual', 'Unknown',
```

```
'Financial Institution', 'Religious Organization'], dtype=object)
```

[46]:
```
df=df_victim[((df_victim.age_num=='') & (df.victim_type.isin(['Law Enforcement␣
 ↪Officer', 'Individual'])))]
print('Number of records with empty string in age_num and Individual or Law␣
 ↪Inforcement victim type: {}'.format(len(df)))
```

```
Number of records with empty string in age_num and Individual or Law Inforcement
victim type: 41406
```

1. The empty string values in the age_num column of victims with types **'Society/Public', 'Business', 'Government', 'Other','Unknown', Financial Institution', and 'Religious Organization'** will be replaced with 999. 2. The empty string values in the age_num column of victims with types **'Law Enforcement Officer', 'Individual'** AND age_group equal 'Unknown' will be replaced with 999. 3. The empty string values in the age_num column of victims with of types **'Law Enforcement Officer', 'Individual'** AND age_group in ('7-364 Days Old','Under 24 Hours','1-6 Days Old') will be replaced with 0. 4. The empty string values in the age_num column of victims with of types **'Law Enforcement Officer', 'Individual'** AND age_group 'Over 98 Years Old' will be replaced with 99.

[47]:
```
df_victim.loc[((df_victim.age_num=='')
               &df_victim.victim_type.isin(['Society/Public','Business',␣
 ↪'Government','Other','Unknown',
                                            'Financial Institution','Religious␣
 ↪Organization'])), 'age_num'] = '999'
df_victim.loc[((df_victim.age_num=='')
               &(df_victim.victim_type.isin(['Law Enforcement Officer',␣
 ↪'Individual']))
               &(df_victim.age_group.isin(['7-364 Days Old','Under 24␣
 ↪Hours','1-6 Days Old']))), 'age_num'] = '0'

df_victim.loc[((df_victim.age_num=='')
               &(df_victim.victim_type.isin(['Law Enforcement Officer',␣
 ↪'Individual']))
               &(df_victim.age_group=='Over 98 Years Old')), 'age_num'] = '99'

df_victim.loc[((df_victim.age_num=='')
               &(df_victim.victim_type.isin(['Law Enforcement Officer',␣
 ↪'Individual']))
               &(df_victim.age_group=='Unknown')), 'age_num'] = '999'
```

sex_code, empty string values

[48]:
```
df=df_victim[df_victim.sex_code=='']
print('Number of records with empty string in sex_code: {}'.format(len(df)))
df.victim_type.unique()
```

```
Number of records with empty string in sex_code: 991009
```

[48]:
```
array(['Society/Public', 'Business', 'Government', 'Other', 'Unknown',
       'Financial Institution', 'Religious Organization'], dtype=object)
```

The empty string values in the sex_code column of victims with of types **'Society/Public', 'Business', 'Government', 'Other','Unknown', Financial Institution', and 'Religious Organization'** will be replaced with **'NA'** value. Due to the fact that these victim types are the only types of sex_code empty string records, all sex_code empty string values will replaced with **'NA'**.

[49]:
```
df_victim.loc[df_victim.sex_code=='', 'sex_code'] = 'NA'
```

resident_status_code, empty string values

[50]:
```
df=df_victim[df_victim.resident_status_code=='']
print('Number of records with empty string in resident_status_code: {}'.
 ↪format(len(df)))
df.victim_type.unique()
```

```
Number of records with empty string in resident_status_code: 1068153
```

[50]:
```
array(['Society/Public', 'Business', 'Government', 'Other', 'Unknown',
       'Financial Institution', 'Religious Organization', 'Individual',
       'Law Enforcement Officer'], dtype=object)
```

[51]:
```
df=df_victim[((df_victim.resident_status_code=='') & (df.victim_type.isin(['Law␣
 ↪Enforcement Officer', 'Individual'])))]
print('Number of records with empty string in resident_status_code and␣
 ↪Individual or \
Law Inforcement victim type: {}'.format(len(df)))
```

```
Number of records with empty string in resident_status_code and Individual or
Law Inforcement victim type: 77144
```

1. The empty string values in the resident_status_code column of victims with of types **'Society/Public', 'Business', 'Government', 'Other','Unknown', Financial Institution', and 'Religious Organization'** will be replaced with **'NA'** value 2. The empty string values in the resident_status_code column of victims with of types **'Law Enforcement Officer', 'Individual'** will be replaced with **'Unknown'** value

[52]:
```
df_victim.loc[((df_victim.resident_status_code=='')
               &df_victim.victim_type.isin(['Society/Public','Business',␣
 ↪'Government','Other',
                                            'Unknown','Financial Institution',
                                            'Religious Organization'])),␣
 ↪'resident_status_code'] = 'NA'

df_victim.loc[((df_victim.resident_status_code=='')
               &(df_victim.victim_type.isin(['Law Enforcement Officer',
                                             'Individual']))),␣
 ↪'resident_status_code'] = 'Unknown'
```

Renaming the columns

[53]:
```
df_victim=df_victim.rename(columns={'age_num': 'victim_age', 'sex_code':␣
↪'victim_sex',
                           'resident_status_code':␣
↪'victim_resident_status','race': 'victim_race',
                          'age_group':'victim_age_group','ethnicity':
↪'victim_ethnicity'})
```

[54]:
```
empty_string_count(df_victim)
```

```
Column victim_id empty string count: 0
Column victim_id null values count: 0
**************************************************
Column incident_id empty string count: 0
Column incident_id null values count: 0
**************************************************
Column victim_age empty string count: 0
Column victim_age null values count: 0
**************************************************
Column victim_sex empty string count: 0
Column victim_sex null values count: 0
**************************************************
Column victim_resident_status empty string count: 0
Column victim_resident_status null values count: 0
**************************************************
Column victim_race empty string count: 0
Column victim_race null values count: 0
**************************************************
Column victim_age_group empty string count: 0
Column victim_age_group null values count: 0
**************************************************
Column victim_ethnicity empty string count: 0
Column victim_ethnicity null values count: 0
**************************************************
Column victim_type empty string count: 0
Column victim_type null values count: 0
**************************************************
Total number of records in the dataframe: 3229640
```

2.2.5 Checking for duplicates, missing values and other abnormalities, offender table

[55]:
```
df_offender.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3197991 entries, 0 to 3197990
Data columns (total 7 columns):
 #   Column       Dtype
---  ------       -----
```

```
 0   offender_id  int64
 1   incident_id  int64
 2   age_num      object
 3   sex_code     object
 4   race         object
 5   age_group    object
 6   ethnicity    object
dtypes: int64(2), object(5)
memory usage: 170.8+ MB
```

[56]:
```
df_offender.head()
```

[56]:

	offender_id	incident_id	age_num	sex_code	race	age_group	ethnicity
0	57702592	51264520	25	Male	White	Age in Years	None
1	57702593	51264521			None	None	None
2	57702595	51264523	20	Male	White	Age in Years	None
3	57702596	51264524			None	None	None
4	57702597	51264525	55	Male	White	Age in Years	None

Checking for duplicates The same person can be an offender in several incidents therefore we are only checking for duplicates with offender_ids AND incident_ids

[57]:
```
df=df_offender[df_offender.duplicated(subset=['offender_id',␣
 ↪'incident_id'],keep=False)].sort_values(by='offender_id')
df
```

[57]:
```
Empty DataFrame
Columns: [offender_id, incident_id, age_num, sex_code, race, age_group,
ethnicity]
Index: []
```

No duplicates found

Checking for empty strings/null values

[58]:
```
empty_string_count(df_offender)
```

```
Column offender_id empty string count: 0
Column offender_id null values count: 0
**************************************************
Column incident_id empty string count: 0
Column incident_id null values count: 0
**************************************************
Column age_num empty string count: 1509300
Column age_num null values count: 0
**************************************************
Column sex_code empty string count: 912428
Column sex_code null values count: 0
**************************************************
```

```
Column race empty string count: 0
Column race null values count: 912428
**************************************************
Column age_group empty string count: 0
Column age_group null values count: 912428
**************************************************
Column ethnicity empty string count: 0
Column ethnicity null values count: 1972733
**************************************************
Total number of records in the dataframe: 3197991
```

Abnormal values, offender table

ethnicity, NaN values

[59]:
```
print('Number of records with NaN values in ethnicity: {}'.
 ↪format(df_offender['ethnicity'].isnull().sum()))
df_offender['ethnicity'].value_counts()
```

```
Number of records with NaN values in ethnicity: 1972733
```

[59]:
```
Not Hispanic or Latino    577692
Unknown                   434094
Hispanic or Latino        213472
Name: ethnicity, dtype: int64
```

The NaN value in the **ethnicity** column of offender table will be replaced with **'Unknown'** value

[60]:
```
df_offender.loc[df_offender.ethnicity.isnull(), 'ethnicity'] = 'Unknown'
```

race, NaN values

[61]:
```
print('Number of records with NaN values in race: {}'.
 ↪format(df_offender['race'].isnull().sum()))
df_offender['race'].value_counts()
```

```
Number of records with NaN values in race: 912428
```

[61]:
```
White                                                1438051
Unknown                                               549611
Black or African American                             270218
Asian                                                  11110
American Indian or Alaska Native                       10566
Asian, Native Hawaiian, or Other Pacific Islander       5175
Native Hawaiian or Other Pacific Islander                832
Name: race, dtype: int64
```

The NaN value in the **race** column of offender table will be replaced with **Unknown** value

[62]:
```
df_offender.loc[df_offender.race.isnull(), 'race'] = 'Unknown'
```

age_group, NaN values

[63]:
```
print('Number of records with NaN values in age_group: {}'.
 ↪format(df_offender['age_group'].isnull().sum()))
df_offender['age_group'].value_counts()
```

```
Number of records with NaN values in age_group: 912428
```

[63]:
```
Age in Years          1688691
Unknown                596172
Over 98 Years Old         700
Name: age_group, dtype: int64
```

[64]:
```
df_offender.loc[df_offender['age_group'].isnull()]
```

[64]:

	offender_id	incident_id	age_num	sex_code	race	age_group	ethnicity
1	57702593	51264521			Unknown	None	Unknown
3	57702596	51264524			Unknown	None	Unknown
7	57702612	51264539			Unknown	None	Unknown
11	57702603	51264530			Unknown	None	Unknown
13	57702605	51264532			Unknown	None	Unknown
…	…	…	…	…	…	…	…
3197957	133652222	117657878			Unknown	None	Unknown
3197970	133657157	117657929			Unknown	None	Unknown
3197974	133652341	117648019			Unknown	None	Unknown
3197980	133652400	117658019			Unknown	None	Unknown
3197981	133652472	117653056			Unknown	None	Unknown

[912428 rows x 7 columns]

The NaN value in the **age_group** column of offender table will be replaced with **Unknown** value. Spot checking the records did not generate any insights. All those offenders are simply not known, never got identified.

[65]:
```
df_offender.loc[df_offender.age_group.isnull(), 'age_group'] = 'Unknown'
```

age_num, empty string values

[66]:
```
df=df_offender[df_offender.age_num=='']
print('Number of records with empty string in age_num: {}'.format(len(df)))
print('Number of records with NaN values in age_group: {}'.
 ↪format(df['age_group'].isnull().sum()))
df['age_group'].value_counts()
```

```
Number of records with empty string in age_num: 1509300
Number of records with NaN values in age_group: 0
```

[66]:
```
Unknown              1508600
Over 98 Years Old        700
Name: age_group, dtype: int64
```

1. The empty string in the **age_num** of offender table with age_group values equal **'Over 98 Years Old'** will be replaced with **99** value 2. The empty string in the **age_num** of offender table with age_group values equal **'Unknown'** will be replaced with **999** value

[67]:
```
df_offender.loc[((df_offender.age_num=='')&(df_offender.age_group=='Over 98␣
 ↪Years Old')), 'age_num'] = '99'

df_offender.loc[((df_offender.age_num=='')
                 &(df_offender.age_group=='Unknown')), 'age_num'] = '999'
```

sex_code, empty string values

[68]:
```
df_offender['sex_code'].value_counts()
```

[68]:
```
Male       1325988
            912428
Female      501641
Unknown     457934
Name: sex_code, dtype: int64
```

The empty string value in the **sex_code** column of offender table will be replaced with **'Unknown'** value

[69]:
```
df_offender.loc[df_offender.sex_code=='', 'sex_code'] = 'Unknown'
```

Renaming the columns

[70]:
```
df_offender=df_offender.rename(columns={'age_num': 'offender_age', 'sex_code':␣
 ↪'offender_sex',
                                        'race': 'offender_race', 'age_group':
 ↪'offender_age_group',
                                        'ethnicity':'offender_ethnicity'})
```

[71]:
```
empty_string_count(df_offender)
```

```
Column offender_id empty string count: 0
Column offender_id null values count: 0
**************************************************
```

```
Column incident_id empty string count: 0
Column incident_id null values count: 0
**************************************************
Column offender_age empty string count: 0
Column offender_age null values count: 0
**************************************************
Column offender_sex empty string count: 0
Column offender_sex null values count: 0
**************************************************
Column offender_race empty string count: 0
Column offender_race null values count: 0
**************************************************
Column offender_age_group empty string count: 0
Column offender_age_group null values count: 0
**************************************************
Column offender_ethnicity empty string count: 0
Column offender_ethnicity null values count: 0
**************************************************
Total number of records in the dataframe: 3197991
```

2.2.6 Checking for duplicates, missing values and other abnormalities, weapon table

[72]:
```
df_weapon.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 551049 entries, 0 to 551048
Data columns (total 2 columns):
 #   Column      Non-Null Count   Dtype 
---  ------      --------------   ----- 
 0   offense_id  551049 non-null  int64 
 1   weapon      551049 non-null  object
dtypes: int64(1), object(1)
memory usage: 8.4+ MB
```

[73]:
```
empty_string_count(df_weapon)
```

```
Column offense_id empty string count: 0
Column offense_id null values count: 0
**************************************************
Column weapon empty string count: 0
Column weapon null values count: 0
**************************************************
Total number of records in the dataframe: 551049
```

[74]:
```
# Checking for duplicates in offense_id column
df=df_weapon[df_weapon.duplicated(subset=['offense_id'],keep=False)].
 ↪sort_values(by='offense_id')
df
```

[74]:
```
        offense_id                 weapon
14148     51643793  Non-automatic firearm
14149     51643793           Other weapon
14002     51646792           Other weapon
14003     51646792           Other weapon
13978     51646830  Non-automatic firearm
…              …                      …
528537   148659366  Non-automatic firearm
528538   148659366           Other weapon
528539   148659366           Other weapon
528614   148660117           Other weapon
528613   148660117  Non-automatic firearm

[19709 rows x 2 columns]
```

There can be several types of weapons used in one offense. For the sake of simplicity I will drop duplicates from the table.

[75]:
```
df_weapon=df_weapon.drop_duplicates(subset=['offense_id'],keep='last')
```

2.2.7 Checking for duplicates, missing values and other abnormalities, bias table

[76]:
```
df_bias.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3201158 entries, 0 to 3201157
Data columns (total 2 columns):
 #   Column      Dtype
---  ------      -----
 0   offense_id  int64
 1   bias_name   object
dtypes: int64(1), object(1)
memory usage: 48.8+ MB
```

[77]:
```
empty_string_count(df_bias)
```

```
Column offense_id empty string count: 0
Column offense_id null values count: 0
**************************************************
Column bias_name empty string count: 0
Column bias_name null values count: 0
**************************************************
Total number of records in the dataframe: 3201158
```

[78]:
```
# Checking for duplicates in offense_id column
df=df_bias[df_bias.duplicated(subset=['offense_id'],keep=False)].
 ↪sort_values(by='offense_id')
df
```

[78]:

	offense_id	bias_name
2060439	111048055	Anti-White
2060440	111048055	Anti-Jewish
1926231	111048057	Anti-White
1926232	111048057	Anti-Jewish
1916086	111048061	Anti-White
1916087	111048061	Anti-Jewish
2060448	111048070	Anti-Hispanic or Latino
2060447	111048070	Anti-Multi-Racial Group
2060446	111048070	Anti-Black or African American
2060445	111048070	Anti-White
2060443	111048071	Anti-Multi-Racial Group
2060444	111048071	Anti-Hispanic or Latino
2060441	111048071	Anti-White
2060442	111048071	Anti-Black or African American
2029958	111048073	Anti-Female Homosexual (Lesbian)
2029957	111048073	Anti-Jewish
2029956	111048073	Anti-White
2755767	123052012	Anti-Black or African American
2755768	123052012	Anti-Islamic (Muslem)
3114725	132470461	Anti-Black or African American
3114726	132470461	Anti-Jewish
2827001	133862508	Anti-Multi-Racial Group
2827002	133862508	Anti-Female Homosexual (Lesbian)
3070181	146759794	Anti-Black or African American
3070182	146759794	Anti-Male Homosexual (Gay)

[79]:
```
df_bias.duplicated(subset='offense_id').sum()
```

[79]:
```
15
```

There can be several types of biases in one offense. The number of duplicates is low. For the sake of simplicity I will drop duplicates from the table.

[80]:
```
df_bias=df_bias.drop_duplicates(subset=['offense_id'],keep='last')
```

2.2.8 Checking for duplicates, missing values and other abnormalities, relationship table

[81]:
```
df_rel.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 794157 entries, 0 to 794156
Data columns (total 3 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   victim_id          794157 non-null  int64
 1   offender_id        794157 non-null  int64
 2   relationship_name  791868 non-null  object
```

```
dtypes: int64(2), object(1)
memory usage: 18.2+ MB
```

[82]:
```
empty_string_count(df_rel)
```

```
Column victim_id empty string count: 0
Column victim_id null values count: 0
**************************************************
Column offender_id empty string count: 0
Column offender_id null values count: 0
**************************************************
Column relationship_name empty string count: 0
Column relationship_name null values count: 2289
**************************************************
Total number of records in the dataframe: 794157
```

[83]:
```
df_rel['relationship_name'].value_counts()
```

[83]:
```
Victim Was Stranger                          168712
Relationship Unknown                         133504
Victim Was Boyfriend/Girlfriend              101800
Victim Was Acquaintance                       92034
Victim was Otherwise Known                    77439
Victim Was Spouse                             48593
Victim Was Offender                           29886
Victim Was Child                              24853
Victim Was Friend                             19718
Victim Was Parent                             16199
Victim Was Other Family Member                13803
Victim Was Sibling                            13440
Victim Was Neighbor                            9883
Victim was Ex-Spouse                           8359
Victim Was Common-Law Spouse                   8189
Homosexual Relationship                        4639
Victim Was Stepchild                           4326
Victim Was Child of Boyfriend or Girlfriend    3281
Victim Was In-law                              2984
Victim Was Stepparent                          2150
Victim Was Grandchild                          2030
Victim was Employee                            1562
Victim Was Grandparent                         1471
Victim Was Stepsibling                         1151
Victim was Employer                            1065
Victim Was Babysittee                           797
Name: relationship_name, dtype: int64
```

[84]:
```
# Replacing NULL values in relationship_name to 'Relationship Unknown'
```

```
df_rel.loc[df_rel.relationship_name.isnull(), 'relationship_name'] =␣
↪'Relationship Unknown'
```

[85]:
```
# Checking for duplicates in offense_id column
df=df_rel[df_rel.duplicated(subset=['victim_id','offender_id'],keep=False)].
↪sort_values(by='victim_id')
df
```

[85]:
```
Empty DataFrame
Columns: [victim_id, offender_id, relationship_name]
Index: []
```

2.3 Part III, combining the DataFrames

2.3.1 DFs Info

[86]:
```
df_incident.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2819189 entries, 0 to 2819462
Data columns (total 6 columns):
 #   Column          Dtype
---  ------          -----
 0   agency_id       int64
 1   incident_id     int64
 2   incident_hour   int64
 3   primary_county  object
 4   icpsr_zip       object
 5   timestamp       datetime64[ns]
dtypes: datetime64[ns](1), int64(3), object(2)
memory usage: 150.6+ MB
```

[87]:
```
with open('data/pickled_dataframes/incident_clean.pickle', 'wb') as f:
    pickle.dump(df_incident, f)
```

[88]:
```
df_offense.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3201143 entries, 0 to 3201142
Data columns (total 6 columns):
 #   Column                Dtype
---  ------                -----
 0   offense_id            int64
 1   incident_id           int64
 2   location_name         object
 3   offense_name          object
 4   crime_against         object
 5   offense_category_name  object
```

```
dtypes: int64(2), object(4)
memory usage: 146.5+ MB
```

[89]:
```
with open('data/pickled_dataframes/offense_clean.pickle', 'wb') as f:
    pickle.dump(df_offense, f)
```

[90]:
```
df_offender.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3197991 entries, 0 to 3197990
Data columns (total 7 columns):
 #   Column              Dtype
---  ------              -----
 0   offender_id         int64
 1   incident_id         int64
 2   offender_age        object
 3   offender_sex        object
 4   offender_race       object
 5   offender_age_group  object
 6   offender_ethnicity  object
dtypes: int64(2), object(5)
memory usage: 170.8+ MB
```

[91]:
```
with open('data/pickled_dataframes/offender_clean.pickle', 'wb') as f:
    pickle.dump(df_offender, f)
```

[92]:
```
df_victim.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3229640 entries, 0 to 3229639
Data columns (total 9 columns):
 #   Column                 Dtype
---  ------                 -----
 0   victim_id              int64
 1   incident_id            int64
 2   victim_age             object
 3   victim_sex             object
 4   victim_resident_status  object
 5   victim_race            object
 6   victim_age_group       object
 7   victim_ethnicity       object
 8   victim_type            object
dtypes: int64(2), object(7)
memory usage: 221.8+ MB
```

[93]:
```
with open('data/pickled_dataframes/victim_clean.pickle', 'wb') as f:
    pickle.dump(df_victim, f)
```

[94]:
```
df_weapon.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 540940 entries, 0 to 551048
Data columns (total 2 columns):
 #   Column      Non-Null Count   Dtype
---  ------      --------------   -----
 0   offense_id  540940 non-null  int64
 1   weapon      540940 non-null  object
dtypes: int64(1), object(1)
memory usage: 12.4+ MB
```

[95]:
```
with open('data/pickled_dataframes/weapon_clean.pickle', 'wb') as f:
    pickle.dump(df_weapon, f)
```

[96]:
```
df_weapon.weapon.value_counts()
```

[96]:
```
Non-automatic firearm    420917
Other weapon             104428
Unknown                   10189
Unarmed                    2803
Automatic firearm          2603
Name: weapon, dtype: int64
```

[97]:
```
df_bias.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3201143 entries, 0 to 3201157
Data columns (total 2 columns):
 #   Column      Dtype
---  ------      -----
 0   offense_id  int64
 1   bias_name   object
dtypes: int64(1), object(1)
memory usage: 73.3+ MB
```

[98]:
```
with open('data/pickled_dataframes/bias_clean.pickle', 'wb') as f:
    pickle.dump(df_bias, f)
```

[99]:
```
df_rel.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 794157 entries, 0 to 794156
Data columns (total 3 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   victim_id          794157 non-null  int64
 1   offender_id        794157 non-null  int64
 2   relationship_name  794157 non-null  object
dtypes: int64(2), object(1)
memory usage: 18.2+ MB
```

[100]:
```
with open('data/pickled_dataframes/rel_clean.pickle', 'wb') as f:
    pickle.dump(df_rel, f)
```

1. Offense, incident, bias and weapon DataFrames will be combined into one for the Times-series analysis 2. Offender, victim and relationship DataFrames will be set aside for the dashboard.

2.3.2 Combining Incident, Offense, Bias and Weapon DataFrames

[101]:
```
df_full=df_offense.merge(df_incident, how='left', on='incident_id')
df_full.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3201143 entries, 0 to 3201142
Data columns (total 11 columns):
 #   Column                 Dtype
---  ------                 -----
 0   offense_id             int64
 1   incident_id            int64
 2   location_name          object
 3   offense_name           object
 4   crime_against          object
 5   offense_category_name  object
 6   agency_id              int64
 7   incident_hour          int64
 8   primary_county         object
 9   icpsr_zip              object
 10  timestamp              datetime64[ns]
dtypes: datetime64[ns](1), int64(4), object(6)
memory usage: 293.1+ MB
```

[102]:
```
df_full=df_full.merge(df_bias, how='left', on='offense_id')
df_full.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3201143 entries, 0 to 3201142
Data columns (total 12 columns):
 #   Column                 Dtype
---  ------                 -----
 0   offense_id             int64
 1   incident_id            int64
 2   location_name          object
 3   offense_name           object
 4   crime_against          object
 5   offense_category_name  object
 6   agency_id              int64
 7   incident_hour          int64
 8   primary_county         object
 9   icpsr_zip              object
 10  timestamp              datetime64[ns]
```

```
 11  bias_name              object
dtypes: datetime64[ns](1), int64(4), object(7)
memory usage: 317.5+ MB
```

[103]:
```
df_full=df_full.merge(df_weapon, how='left', on='offense_id')
df_full.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3201143 entries, 0 to 3201142
Data columns (total 13 columns):
 #   Column                 Dtype
---  ------                 -----
 0   offense_id             int64
 1   incident_id            int64
 2   location_name          object
 3   offense_name           object
 4   crime_against          object
 5   offense_category_name  object
 6   agency_id              int64
 7   incident_hour          int64
 8   primary_county         object
 9   icpsr_zip              object
 10  timestamp              datetime64[ns]
 11  bias_name              object
 12  weapon                 object
dtypes: datetime64[ns](1), int64(4), object(8)
memory usage: 341.9+ MB
```

[104]:
```
empty_string_count(df_full)
```

```
Column offense_id empty string count: 0
Column offense_id null values count: 0
**************************************************
Column incident_id empty string count: 0
Column incident_id null values count: 0
**************************************************
Column location_name empty string count: 0
Column location_name null values count: 0
**************************************************
Column offense_name empty string count: 0
Column offense_name null values count: 0
**************************************************
Column crime_against empty string count: 0
Column crime_against null values count: 0
**************************************************
Column offense_category_name empty string count: 0
Column offense_category_name null values count: 0
**************************************************
Column agency_id empty string count: 0
```

```
Column agency_id null values count: 0
**************************************************
Column incident_hour empty string count: 0
Column incident_hour null values count: 0
**************************************************
Column primary_county empty string count: 0
Column primary_county null values count: 0
**************************************************
Column icpsr_zip empty string count: 0
Column icpsr_zip null values count: 0
**************************************************
Column timestamp empty string count: 0
Column timestamp null values count: 0
**************************************************
Column bias_name empty string count: 0
Column bias_name null values count: 0
**************************************************
Column weapon empty string count: 0
Column weapon null values count: 2660203
**************************************************
Total number of records in the dataframe: 3201143
```

[105]:
```
df_full.weapon.unique()
```

[105]:
```
array(['Non-automatic firearm', nan, 'Other weapon', 'Unknown', 'Unarmed',
       'Automatic firearm'], dtype=object)
```

[106]:
```
df=df_full[df_full.weapon.isnull()]
df.offense_category_name.unique()
```

[106]:
```
array(['Larceny/Theft Offenses', 'Drug/Narcotic Offenses',
       'Fraud Offenses', 'Destruction/Damage/Vandalism of Property',
       'Burglary/Breaking & Entering', 'Assault Offenses', 'Sex Offenses',
       'Arson', 'Motor Vehicle Theft', 'Pornography/Obscene Material',
       'Counterfeiting/Forgery', 'Bribery', 'Stolen Property Offenses',
       'Prostitution Offenses', 'Embezzlement', 'Gambling Offenses',
       'Animal Cruelty'], dtype=object)
```

[107]:
```
# Replacing NaN values in weapon column by 'NA'. Offenses associated with␣
 ↪weapon NaN values seem
# to be offenses with no weapon necessary

df_full.loc[df_full.weapon.isnull(), 'weapon'] = 'NA'
```

[108]:
```
df_full.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3201143 entries, 0 to 3201142
```

```
Data columns (total 13 columns):
 #   Column                 Dtype
---  ------                 -----
 0   offense_id             int64
 1   incident_id            int64
 2   location_name          object
 3   offense_name           object
 4   crime_against          object
 5   offense_category_name  object
 6   agency_id              int64
 7   incident_hour          int64
 8   primary_county         object
 9   icpsr_zip              object
 10  timestamp              datetime64[ns]
 11  bias_name              object
 12  weapon                 object
dtypes: datetime64[ns](1), int64(4), object(8)
memory usage: 341.9+ MB
```

[109]:
```
with open('data/pickled_dataframes/df_full_clean.pickle', 'wb') as f:
    pickle.dump(df_full, f)
```

3 EXPLORE

3.1 EDA

3.1.1 General information about the data

[110]:
```
print('There are {} records of offenses in Colorado between 2009 and 2019'.
 ↪format(len(df_full)))
```

```
There are 3201143 records of offenses in Colorado between 2009 and 2019
```

[111]:
```
df_full.nunique()
```

[111]:
```
offense_id              3201143
incident_id             2819189
location_name                46
offense_name                 51
crime_against                 4
offense_category_name        23
agency_id                   249
incident_hour                25
primary_county               64
icpsr_zip                   195
timestamp                  4017
bias_name                    30
weapon                        6
```

```
dtype: int64
```

Plotting crime rate in different offense categories

[112]:
```
freq='W'

df_x = df_full.groupby(['offense_category_name', pd.Grouper(key='timestamp',
 ↪freq=freq)])['offense_category_name'].agg(['count']).reset_index()
df_x = df_x.sort_values(by=['timestamp', 'count'])
df_x
```

[112]:

	offense_category_name	timestamp	count
5845	Homicide Offenses	2009-01-04	1
8255	Pornography/Obscene Material	2009-01-04	1
1317	Bribery	2009-01-04	2
4690	Extortion/Blackmail	2009-01-04	2
8823	Prostitution Offenses	2009-01-04	2
…	…	…	…
4114	Drug/Narcotic Offenses	2020-01-05	120
8254	Motor Vehicle Theft	2020-01-05	126
1316	Assault Offenses	2020-01-05	163
3539	Destruction/Damage/Vandalism of Property	2020-01-05	242
7679	Larceny/Theft Offenses	2020-01-05	481

[11691 rows x 3 columns]

[113]:
```
colors_dark24=px.colors.qualitative.Dark24
colors_dark24=colors_dark24[:-1]
crime_categories=['Assault Offenses', 'Larceny/Theft Offenses',
 'Drug/Narcotic Offenses', 'Fraud Offenses',
 'Destruction/Damage/Vandalism of Property',
 'Burglary/Breaking & Entering', 'Sex Offenses',
 'Arson', 'Motor Vehicle Theft', 'Kidnapping/Abduction',
 'Weapon Law Violations', 'Robbery',
 'Pornography/Obscene Material', 'Counterfeiting/Forgery',
 'Bribery', 'Stolen Property Offenses', 'Prostitution Offenses',
 'Homicide Offenses', 'Extortion/Blackmail',
 'Embezzlement', 'Gambling Offenses',
 'Human Trafficking', 'Animal Cruelty']

color_discrete_map_=dict(zip(crime_categories,colors_dark24))
```

[114]:
```
fig1 = px.line(df_x, x='timestamp', y='count', color='offense_category_name',
              color_discrete_map=color_discrete_map_,
labels={ "timestamp": "Date",  "count": "Number of Offenses",
 ↪"offense_category_name": "Offense Category"},
      title='Number of Offenses in Different Crime Categories',
```

```
template="plotly_dark"
             )

fig1.update_layout(width=1000,
                   height=800)

fig1.update_layout(
    xaxis=dict(
#         rangeselector=dict(
#             buttons=list([
#                 dict(count=1,
#                      step="month",
#                      stepmode='backward'),
#             ])),
        rangeslider=dict(
            visible=True
        ),
    )
)
fig1.show()
```

[115]:
```
with open('images/pickled_figs/crime_cat.pickle', 'wb') as f:
    pickle.dump(fig1, f)
```

Number of Offenses in Weapon Categories

[116]:
```
df_weapon = df_full.groupby(['weapon']).count().sort_values(['offense_id'],␣
↪ascending=False).reset_index()
df_weapon = df_weapon[df_weapon ['weapon'] != 'NA']


fig1 = px.bar(df_weapon, x='weapon',  y='offense_id', color='weapon',
              color_discrete_sequence=px.colors.qualitative.Set1,
             labels={"weapon": "Weapon",  "offense_id": "Number of Offenses"},
             title='Weapons Used in Offenses',
template="plotly_dark"
             )

fig1.update_layout(width=1000,
                   height=700,
                   bargap=0.05)
fig1.show()
```

[117]:
```
with open('images/pickled_figs/weapons.pickle', 'wb') as f:
    pickle.dump(fig1, f)
```

[118]:
```
df_crime_against = df_full.groupby(['crime_against']).count().
↪sort_values(['offense_id'], ascending=False).reset_index()
```

```
df_crime_against  = df_crime_against [df_crime_against  ['crime_against'] !=␣
↪'Not a Crime']


fig1 = px.bar(df_crime_against, x='crime_against',  y='offense_id',␣
↪color='crime_against',
             color_discrete_sequence=px.colors.qualitative.Set1,
            labels={"crime_against": "Crime Against",  "offense_id": "Number of␣
↪Offenses"},
            title='Crime Against Offenses',
template="plotly_dark"
             )

fig1.update_layout(width=1000,
                   height=700,
                   bargap=0.05)
fig1.show()
```

Crime rate per zip codes

[119]:
```
df_zip = df_full.groupby(['icpsr_zip']).count().sort_values(['offense_id'],␣
↪ascending=False).reset_index()


fig1 = px.bar(df_zip[:15], x='icpsr_zip',  y='offense_id', color='icpsr_zip',
              color_discrete_sequence=␣
↪["#800000","#990000","#A52A2A","#B22222","#DC143C","#CD5C5C","#FF0000","#FF6347",
                                      ␣
↪"#FF7F50","#FA8072","#F08080","#FFA074","#FFCCE5","#FFCCCC","#FFE5CC"],
            labels={"icpsr_zip": "Zip Codes",  "offense_id": "Number of␣
↪Offenses"},
             title='Zip Codes Reporting the Highest Offense Numbers',
template="plotly_dark"
             )

fig1.update_layout(width=1000,
                   height=700,
                   bargap=0.05)
fig1.show()
```

[120]:
```
with open('images/pickled_figs/zips.pickle', 'wb') as f:
    pickle.dump(fig1, f)
```

Crime rate per county

[121]:
```
df_county = df_full.groupby(['primary_county']).count().
↪sort_values(['offense_id'], ascending=False).reset_index()
```

```
fig1 = px.bar(df_county[:15], y='primary_county',  x='offense_id',␣
↪color='primary_county',  orientation='h',
              color_discrete_sequence=␣
↪["#800000","#990000","#A52A2A","#B22222","#DC143C","#CD5C5C","#FF0000","#FF6347",
                                        ␣
↪"#FF7F50","#FA8072","#F08080","#FFA074","#FFCCE5","#FFCCCC","#FFE5CC"],
            labels={"primary_county": "County",  "offense_id": "Number of␣
↪Offenses"},
             title='Counties with the Highest Offense Numbers',
template="plotly_dark"
             )

fig1.update_layout(width=1000,
                   height=700,
                   bargap=0.05)
fig1.show()
```

[122]:
```
with open('images/pickled_figs/counties.pickle', 'wb') as f:
    pickle.dump(fig1, f)
```

Crime rate over day hours

[123]:
```
df_hour = df_full.groupby(['incident_hour']).count().
↪sort_values(['offense_id'], ascending=False).reset_index()
df_hour = df_hour[df_hour ['incident_hour'] != 25]
```

[124]:
```
df_hour['hr_str']=df_hour['incident_hour'].astype(str)
```

[125]:
```
df_hour['hr_str']=df_hour['hr_str'].map({'0':'12 AM','1':'1 AM','2':'2 AM','3':
↪'3 AM',
                                         '4':'4 AM','5':'5 AM','6':'6 AM','7':'7 AM',
                                         '8':'8 AM','9':'9 AM','10':'10 AM','11':'11␣
↪AM',
                                         '12':'12 PM','13':'1 PM','14':'2 PM','15':'3␣
↪PM',
                                         '16':'4 PM','17':'5 PM','18':'6 PM','19':'7␣
↪PM',
                                         '20':'8 PM','21':'9 PM','22':'10 PM','23':'11␣
↪PM'})
df_hour.head()
```

[125]:

	incident_hour	offense_id	incident_id	location_name	offense_name	\
0	0	200701	200701	200701	200701	
1	12	185895	185895	185895	185895	
2	17	182505	182505	182505	182505	
3	16	173320	173320	173320	173320	

```
4              15       172326        172326          172326        172326

   crime_against  offense_category_name  agency_id  primary_county  icpsr_zip  \
0         200701                 200701     200701          200701     200701
1         185895                 185895     185895          185895     185895
2         182505                 182505     182505          182505     182505
3         173320                 173320     173320          173320     173320
4         172326                 172326     172326          172326     172326

   timestamp  bias_name  weapon hr_str
0     200701     200701  200701  12 AM
1     185895     185895  185895  12 PM
2     182505     182505  182505   5 PM
3     173320     173320  173320   4 PM
4     172326     172326  172326   3 PM
```

[126]:
```
fig1 = px.bar(df_hour, x='hr_str',  y='offense_id', color='hr_str',
              color_discrete_map={'12 AM':'red','1 AM':"#808080",'2 AM':
 ↪"#808080",'3 AM':"#808080",
                                  '4 AM':"#808080",'5 AM':"#808080",'6 AM':
 ↪"#808080",'7 AM':"#808080",
                                  '8 AM':'red','9 AM':"#808080",'10 AM':
 ↪"#808080",'11 AM':"#808080",
                                  '12 PM':'red','1 PM':"#808080",'2 PM':
 ↪"#808080",'3 PM':"#808080",
                                  '4 PM':"#808080",'5 PM':'red','6 PM':
 ↪"#808080",'7 PM':"#808080",
                                  '8 PM':"#808080",'9 PM':"#808080",'10 PM':
 ↪"#808080",'11 PM':"#808080"},
             category_orders={'hr_str': ['12 AM', '1 AM', '2 AM', '3 AM','4␣
 ↪AM','5 AM','6 AM','7 AM','8 AM','9 AM',
                                         '10 AM','11 AM','12 PM','1 PM','2␣
 ↪PM','3 PM','4 PM','5 PM','6 PM','7 PM',
                                         '8 PM','9 PM','10 PM','11 PM']},
             labels={'hr_str': "Hour",  "offense_id": "Number of Offenses"},
               title='Most Dangerous Hours',
template="plotly_dark"
              )

fig1.update_layout(width=1000,
                   height=700,
                   bargap=0.05)
fig1.show()
```

[127]:
```
with open('images/pickled_figs/hours.pickle', 'wb') as f:
    pickle.dump(fig1, f)
```

Geography of crime

[128]:
```
# fig2=map_choropleth_location(df_county, 'primary_county', 'County',␣
↪'offense_id', 'Number of Offenses',
#                              CO_county_json, 'properties.name', 'Number of␣
↪Offenses per County')
```

[129]:
```
# with open('images/pickled_figs/county_map.pickle', 'wb') as f:
#     pickle.dump(fig2, f)
```

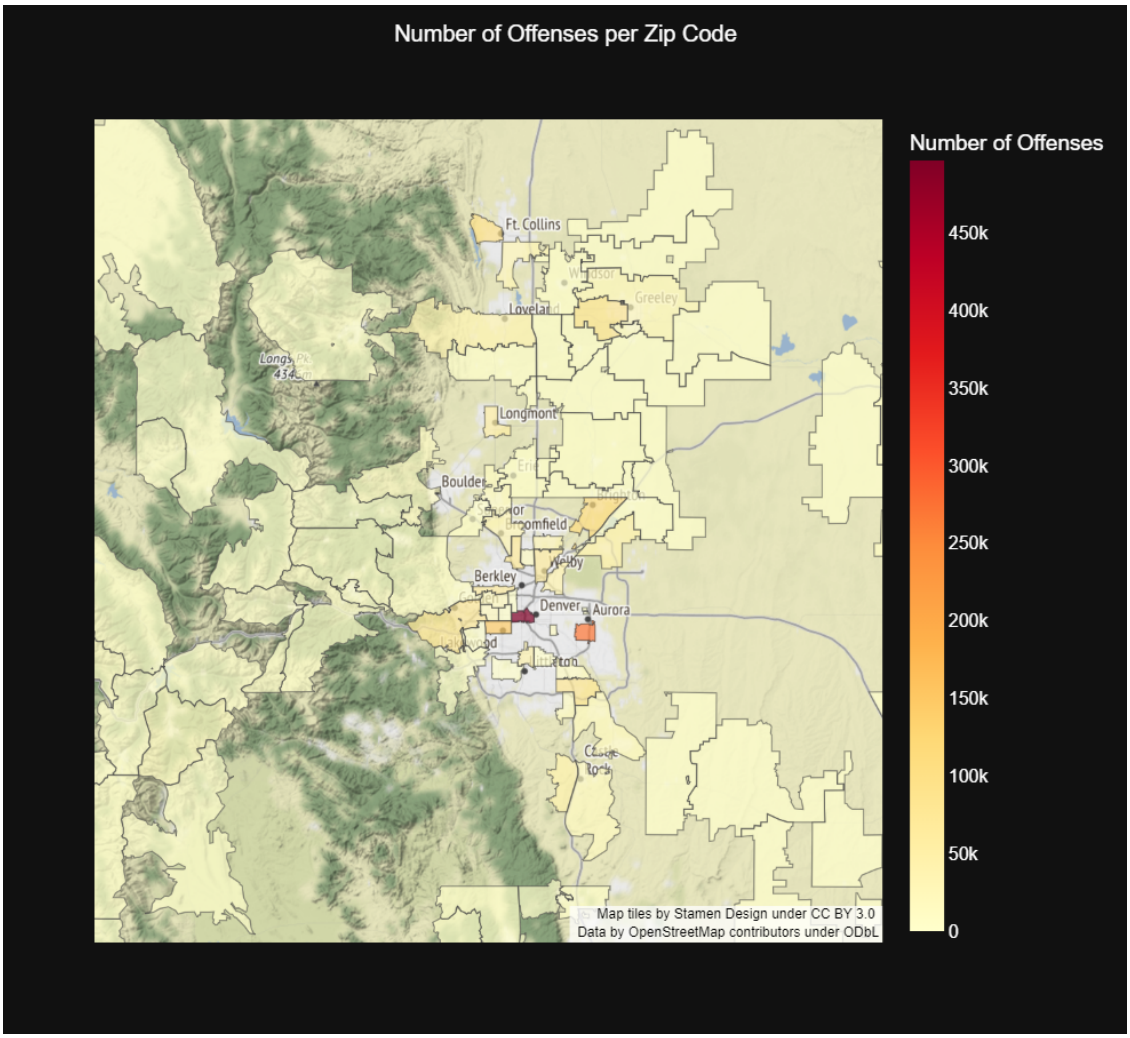
[130]:
```
with open('images/pickled_figs/county_map.pickle', 'rb') as f:
    fig2=pickle.load(f)
fig2.show()
```

[131]:
```
# fig2=map_choropleth_location(df_zip, 'icpsr_zip', 'Zip code', 'offense_id',␣
↪'Number of Offenses',
#                              CO_zip_json, 'properties.ZCTA5CE10', 'Number of␣
↪Offenses per Zip Code')
```

[132]:
```
# with open('images/pickled_figs/zip_map.pickle', 'wb') as f:
#     pickle.dump(fig2, f)
```

[133]:
```
# with open('images/pickled_figs/zip_map.pickle', 'rb') as f:
#     fig2=pickle.load(f)
# fig2.show()
```

To reduce the size of the notebook the following map is a png image of the live plotly express choropleth plot. In order to generate the live plot uncomment the cell above and run it.



It takes ~1.5 minutes to run this notebook

General crime rate modeling is in part III notebook. I decided to split them for better manageability.

[ ]: