In [59]:

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-p
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all f

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets pres
# You can also write temporary files to /kaggle/temp/, but they won't be saved outsic
```

```
/kaggle/input/Crime-baltimore/Part_1_Crime_Data.csv
```

Table of Contents

In [60]:

```
#visual tools:
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from plotly.offline import init_notebook_mode, plot, iplot
import plotly as py
init_notebook_mode(connected=True)
import plotly.graph_objs as go
import plotly.graph_objs as go
import plotly.tools as tls
#import missingno as msno
import pandas as pd

#import cufflinks as cf
import ydata_profiling
import folium
import datetime
```

In [61]:
```
def enable_plotly_in_cell():
  import IPython
  from plotly.offline import init_notebook_mode
  display(IPython.core.display.HTML('''<script src="/static/components/requirejs/requ
  init_notebook_mode(connected=False)


#data set:
df_crime = pd.read_csv("/kaggle/input/Crime-baltimore/Part_1_Crime_Data.csv")
```

```
/tmp/ipykernel_32/1636894786.py:9: DtypeWarning:

Columns (12) have mixed types. Specify dtype option on import or set low_memory=Fals
e.
```

Introduction

In this Notebook I will analyse "Part1_Crime_Data.csv" dataset taken from https://data.baltimorecity.gov/: This dataset represents the location and characteristics of major (Part 1) crime against persons such as homicide, shooting, robbery, aggravated assault etc. within the City of Baltimore. Data is updated weekly. This is an exploratory analysis.

The data was last updated May 17, 2023, the original csv file contains 565,726 records and 20 columns.

Attributes (columns) : CCNO, CrimeDateTime, Location, Description, Inside_Outside, Weapon, Post, Gender, Age, Race, Ethnicity, District, Neighborhood, Latitude, Longitude, Geolocation, Premise, Total_incidents,

Data Preparation - Data cleaning

He I'm checking the data types of the columns, handling missing values and handling time values.

In [62]:
```
len(df_crime.columns)
```

Out[62]:
```
20
```

In [63]:

```
##code below was taken from -Exploratory Analysis of Vancouver Crime Data by KANGBO L

def missing_value_describe(data):
    # check missing values in training data
    missing_value_stats = (data.isnull().sum() / len(data)*100)
    missing_value_col_count = sum(missing_value_stats > 0)
    missing_value_stats = missing_value_stats.sort_values(ascending=False)[:missing_v
    print("Number of columns with missing values:", missing_value_col_count)
    if missing_value_col_count != 0:
        # print out column names with missing value percentage
        print("\nMissing percentage (desceding):")
        print(missing_value_stats)
    else:
        print("No missing data!!!")
missing_value_describe(df_crime)
```

```
Number of columns with missing values: 13

Missing percentage (desceding):
Ethnicity          95.199104
Weapon             76.887395
Age                20.184155
Premise            18.571681
Inside_Outside     18.510359
Gender             16.431729
Race                2.431395
Neighborhood        2.333929
Post                2.333071
District            2.295782
Location            0.495339
Longitude           0.146294
Latitude            0.146294
dtype: float64
```

We need to replace the null cells with the appropriate

Missing percentages

In [64]:

```
df_crime['Age'].describe()
```

Out[64]:

```
count    836929.000000
mean         37.623839
std          39.259944
min       -7979.000000
25%          26.000000
50%          34.000000
75%          49.000000
max        8251.000000
Name: Age, dtype: float64
```

In [65]:

```
#replace the null values
# As HOUR is a float data type, I'm filling with a dummy value of '99'. For others, f

df_crime['Inside_Outside'].fillna('N/A', inplace = True)
df_crime['Weapon'].fillna('N/A', inplace = True)
df_crime['Ethnicity'].fillna('N/A', inplace = True)
df_crime['Premise'].fillna('N/A', inplace = True)
df_crime['Age'].fillna(37, inplace = True)
df_crime['Post'].fillna('N/A', inplace = True)
df_crime['Neighborhood'].fillna('N/A', inplace = True)
df_crime['District'].fillna('N/A', inplace = True)
df_crime['Race'].fillna('N/A', inplace = True)
df_crime['Location'].fillna('N/A', inplace = True)
df_crime['Longitude'].fillna(99, inplace = True)
df_crime['Latitude'].fillna(99, inplace = True)
df_crime['Gender'].fillna('N/A', inplace = True)
```

In the table below we see that six columns have more than 15% missing data. All the missing cells are replaced by N/A, except for age, age is replaced by the average - 37 years old. Seven columns also have missing data, and they are also filled with N/A except for Longitude and Latitude, which are replaced with 99. These values are only place holders, when we will go into the analysis of specific columns I will drop the rows.

column	Missing \%
Ethnicity	95.199104
Weapon	76.887395
Age	20.184155
Premise	18.571681
Inside_Outside	18.510359
Gender	16.431729

In [66]:

```
#check to see how far the data goes starting from 1949 and see if there no dummy valu
df_crime[df_crime['CrimeDateTime'] < '1950-01-01']
```

Out[66]:

	RowID	CCNO	CrimeDateTime	CrimeCode	Location	Description	Inside_Outside	
561102	561103	22F07001	1922/06/22 13:00:00+00	4E	1100 LIGHT ST	COMMON ASSAULT	Inside	PERS
561103	561104	22F05949	1920/06/18 01:30:00+00	3AO	3700 LEVERTON AVE	ROBBERY	Inside	PERS
561104	561105	22E07562	1202/05/22 10:56:02+00	6J	900 BETHUNE RD	LARCENY	Inside	
561105	561106	23C04992	1023/03/16 12:57:02+00	4B	4600 PEN LUCY RD	AGG. ASSAULT	N/A	PERS

	RowID	CCNO	CrimeDateTime	CrimeCode	Location	Description	Inside_Outside	
561106	561107	23A07816	1023/01/26	4E	3800 FALLSTAFF	COMMON	N/A	PERS

Much of our analysis will be based on dates. The Baltimore website does not specify when they started to collect the crime data, problems may arise when comparing the changes in crime through the years, therefore we need to know if the data collection is consistant and if the years are complete (if we see data collected every month for every year for every category). Before starting the analysis we need to divide the data into years, months and hours, however,when I tried at first it gave me an error. I decided to first check the records before 1950, I quickly realized that some dates were in wrong format. These records were droped.

The results from checking the records show that some values in CrimDateTime are not in the right format and also shows that there are only two records with dates before 1950. All these records need to be deleted.

In [67]:

```
#delete all these dummy values and outlier dates
df_crime= df_crime.drop(df_crime[df_crime['CrimeDateTime'] < '1950-01-01'].index)
```

To analyse the data per year,months and hours I created new columns, before creating the new columns the data type of CrimeDateTime needs to be changed.

In [68]:

```
###Transform to date type so we can create new columns
df_crime["CrimeDateTime"] = df_crime["CrimeDateTime"].astype("datetime64")
```

In [69]:

```
#create new columns for year, month, day, hour, and minutes so we can perform some ar
df_crime['year'] = pd.to_datetime(df_crime["CrimeDateTime"]).dt.year
df_crime['month'] = pd.to_datetime(df_crime["CrimeDateTime"]).dt.month
df_crime['day'] = pd.to_datetime(df_crime["CrimeDateTime"]).dt.day
df_crime['hour'] = pd.to_datetime(df_crime["CrimeDateTime"]).dt.hour
df_crime['minute'] = pd.to_datetime(df_crime["CrimeDateTime"]).dt.minute
```

Here below we run records group by year, this will indicate us what years need to be droped (based on the idea that we have around half a million records, therefore we need thousands of records per year and we need consistant numbers

In [70]:

```
df_crime.groupby(["year"]).size().reset_index(name='counts')
```

Out[70]:

	year	counts
0	1963	1
1	1966	1
2	1969	1
3	1970	1
4	1973	1
5	1975	1

	year	counts
6	1976	1
7	1977	1
8	1978	3
9	1979	1
10	1980	2
11	1981	1
12	1982	3
13	1983	1
14	1984	1
15	1985	1
16	1987	1
17	1988	1
18	1989	1
19	1993	3
20	1994	1
21	1995	4
22	1996	1
23	1998	4
24	1999	5
25	2000	5
26	2001	11
27	2002	15
28	2003	7
29	2004	5
30	2005	3
31	2006	4
32	2007	13
33	2008	12
34	2009	15
35	2010	27
36	2011	48965
37	2012	65955
38	2013	95550

	year	counts
39	2014	90458
40	2015	96142
41	2016	97350
42	2017	104597
43	2018	97200
44	2019	93208
45	2020	72568
46	2021	74756

We can now delete all records before 2011.

In [71]:

```
df_crime= df_crime.drop(df_crime[df_crime['CrimeDateTime'] < '2011-01-01'].index)
```

Our data we need complete years, we need to eliminate years that are incomplete. Here I aggregate the number of months per year to see if every year starting from 2011 has 12 months, if a year does not have 12 months it will be dropped. Here I found out that year 2023 only has 6 months, I kept the 2023 data in case I need to analyse further.

In [72]:

```
df12=df_crime.groupby(["year"]).agg({'month': 'nunique'})

df12[df12["month"]<12]
```

Out[72]:

year	month
2023	6

In [73]:

```
df_crime2013= df_crime[df_crime['CrimeDateTime'] >= '2023-01-01']
df_crime2013
```

Out[73]:

	RowID	CCNO	CrimeDateTime	CrimeCode	Location	Description	Inside_Outside
0	1	23E09497	2023-05-27 01:30:00	4C	1000 STAMFORD RD	AGG. ASSAULT	N/A
1	2	23E09500	2023-05-27 00:00:00	4E	1200 RAMBLEWOOD RD	COMMON ASSAULT	N/A
2	3	23E10022	2023-05-27 12:00:00	6F	2200 LAKE AVE	LARCENY	N/A
3	4	23E10735	2023-05-27 09:00:00	6D	7200 PARK HEIGHTS AVE	LARCENY FROM AUTO	N/A

	RowID	CCNO	CrimeDateTime	CrimeCode	Location	Description	Inside_Outside
4	5	23E09625	2023-05-27 13:00:39	4E	1800 SAINT PAUL ST	COMMON ASSAULT	N/A
...	...	...	...	...	...	...	...
587748	587749	23C03541	2023-03-11 22:00:00	6F	700 VINE ST	LARCENY	N/A
587749	587750	23C04661	2023-03-11 00:00:00	6J	6200 HOLABIRD AVE	LARCENY	N/A
587750	587751	23C03461	2023-03-11 17:01:31	9S	3300 BRIGHTON ST	SHOOTING	Outside
587751	587752	23C03461	2023-03-11 17:01:31	9S	3300 BRIGHTON ST	SHOOTING	Outside
587752	587753	23C03811	2023-03-11 07:00:00	7C	1700 INGRAM RD	AUTO THEFT	N/A

In [74]:

```
##drop 2013 data from the main analysis
df_crime= df_crime.drop(df_crime[df_crime['CrimeDateTime'] >= '2023-01-01'].index)
```

We also need to check if every year contains every type of crime - we assume here that normally every type of crime needs to be reported every year. Below I loop into the years and type of crimes to see which type of crime from which year is missing. I find that in 2011 there are no shootings and no homicide reported. I therefore drop that year.

In [75]:

```
###We also need to make sure that each type of crime has values,
r=df_crime.groupby(["year","Description"]).size().reset_index(name='counts')
Ds=df_crime['Description'].unique()
years=df_crime['year'].unique()
for i in range(len(years)):
    rs= r.loc[r['year'] ==years[i]]
    for j in range(len(Ds)):
        if Ds[j] not in list(rs['Description']):
            print(years[i])
            print(Ds[j])

###below we can see that shooting and Homicide has no values for 2011, so 2011 must b
##our dataframe
```

```
2011
HOMICIDE
2011
SHOOTING
```

In [76]:

```
df_crime= df_crime.drop(df_crime[df_crime['CrimeDateTime'] < '2012-01-01'].index)
```

Exploratory Data Analysis

This section involved exploring the data to gain insights. The analysis includes crimes per type,

In [77]:

```
#dimension of the dataset
print("the dimension:", df_crime.shape)
```

```
the dimension: (966194, 25)
```

In [78]:

```
##quick picture of the number of crimes per type
df_crime['Description'].value_counts()
```

Out[78]:

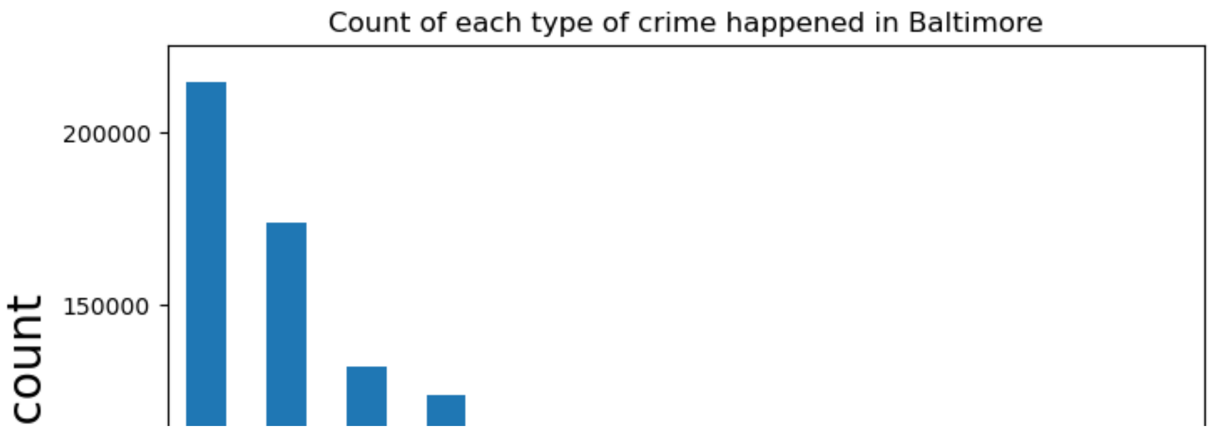
```
LARCENY                  214859
COMMON ASSAULT           173886
BURGLARY                 131727
LARCENY FROM AUTO        123617
AGG. ASSAULT             111463
AUTO THEFT                82859
ROBBERY                   79203
SHOOTING                  12017
ROBBERY - COMMERCIAL      10667
ROBBERY - CARJACKING       8877
HOMICIDE                   6496
RAPE                       6374
ARSON                      4149
Name: Description, dtype: int64
```

In [79]:

```
# crime type distribution in a bar chart
##all years combined , larceny, common assault and bulgary
nameplot = df_crime['Description'].value_counts().plot.bar(title='Count of each type
nameplot.set_xlabel('category',size=20)
nameplot.set_ylabel('crime count',size=20)
```

Out[79]:

```
Text(0, 0.5, 'crime count')
```



The top 3 crimes per type are Larceny, Common Assualt and Bulgary. The 3 type of crimes that appeared the least are homicide, rape and arson. Larceny appears more than 200k, while arson appears only 4149 times which means that Larceny rates are 193% higher than arson.

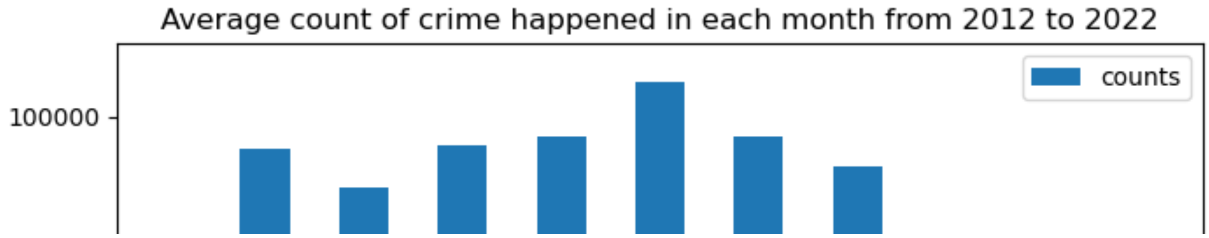
Crime Over Time

In [80]:

```
#quick overview of how many crimes per year
##2012 has least number of

average_crime_count_by_month = df_crime.groupby(["year"]).size().reset_index(name='co
average_crime_count_by_month.reset_index().plot.bar(title='Average count of crime hap
                                                    x = "year", y = "counts",
                                                    figsize=(8,6))
nameplot.set_xlabel('year',size=20)
nameplot.set_ylabel('crime count',size=20)
```

Out[80]:

```
Text(38.0, 0.5, 'crime count')
```



In [81]:
```
counts_year= df_crime.groupby(["year"]).size().reset_index(name='counts').groupby(["y
```

In [82]:
```
count_year_prior= counts_year['counts'].shift()
(counts_year['counts']-count_year_prior)/count_year_prior*100
```

Out[82]:
```
year
2012          NaN
2013    44.871503
2014    -5.329147
2015     6.283579
2016     1.256475
2017     7.444273
2018    -7.071905
2019    -4.106996
2020   -22.144022
2021     3.015103
2022     4.887902
Name: counts, dtype: float64
```

We note from the results that the year 2017 has the highest crime average while the year 2012 has the lowest. We also note that there are two jumps between years for average crime, the first is an increase by 45% from 2012 to 2013, while there is a decrease of 22% from 2019 to 2020.

We can speculate that the data collection in 2012 was maybe incomplete, while the decrease of 22% might be explained by the pandemic.

Now I will create an empty dataframe containing all the crimes per year

In [83]:
```
#has crime decreased over the years in Baltimore

"""
Create empty dataframe to store the crime count over the years in Baltimore
"""
# year values
year_labels = sorted(df_crime["year"].unique())

# crime types
crime_types = sorted(df_crime['Description'].unique().tolist())

# Create the pandas DataFrame
crime_count_by_year = pd.DataFrame(columns =["year"])
crime_count_by_year["year"] = year_labels
crime_count_by_year
```

Out[83]: **year**

	year
0	2012
1	2013
2	2014
3	2015
4	2016
5	2017
6	2018
7	2019
8	2020
9	2021

In [84]:

```
# gather yearly count of crime in Baltimore
for current_type in crime_types:
    print(current_type)
    current_crime = df_crime[df_crime["Description"]==current_type]
    current_crime_counts = current_crime["year"].value_counts(sort=False)
    #print(current_crime_counts)

    current_crime_index = current_crime_counts.index.tolist()




    current_crime_index, current_crime_counts = zip(*sorted(zip(current_crime_index,


    crime_count_by_year[current_type] = current_crime_counts
crime_count_by_year
```

```
AGG. ASSAULT
ARSON
AUTO THEFT
BURGLARY
COMMON ASSAULT
HOMICIDE
LARCENY
LARCENY FROM AUTO
RAPE
ROBBERY
ROBBERY - CARJACKING
ROBBERY - COMMERCIAL
SHOOTING
```

Out[84]:

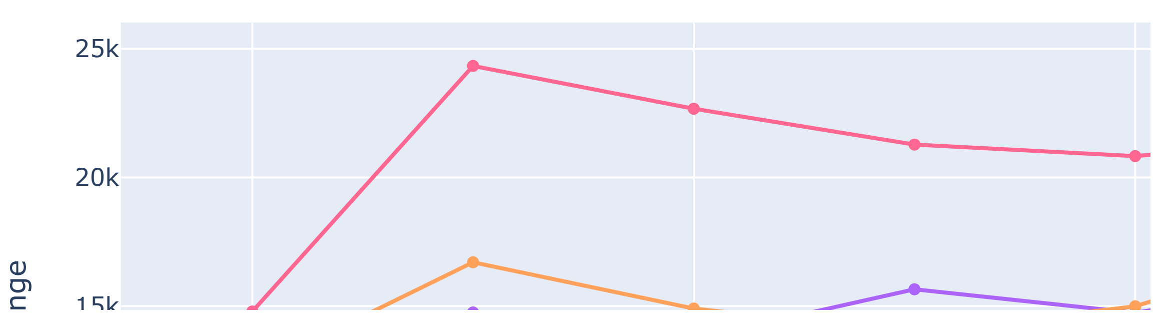
	year	AGG. ASSAULT	ARSON	AUTO THEFT	BURGLARY	COMMON ASSAULT	HOMICIDE	LARCENY	LARCENY FROM AUTO	RAPE
0	2012	6547	317	4911	10946	12497	295	14792	9526	426

	year	AGG. ASSAULT	ARSON	AUTO THEFT	BURGLARY	COMMON ASSAULT	HOMICIDE	LARCENY	LARCENY FROM AUTO	RAPE
1	2013	9094	538	7527	14754	16705	463	24338	13384	546
2	2014	8518	432	7298	13734	14906	422	22674	13432	494
3	2015	9480	584	9124	15654	13968	684	21280	14094	572
4	2016	10262	534	9202	14740	14994	636	20832	13030	590
5	2017	11728	532	9328	16164	17638	684	21608	12372	761
6	2018	11262	254	8436	12436	16896	618	21422	12754	732
7	2019	11470	230	7538	10854	16830	696	21546	11556	634

In [85]:

```
# Create traces
fig = go.Figure()
for current_crime in crime_types:
    current_type_count = crime_count_by_year[current_crime]
    fig.add_trace(
        go.Scatter(
            x=year_labels,
            y=current_type_count,
            mode='lines+markers',
            name=current_crime
        )
    )
# Edit the layout
fig.update_layout(title='Crimes Over the Years in Baltimoe by Type',
                  xaxis_title='Year',
                  yaxis_title='Absolute Change',
                  autosize=True,
                  height=570
                 )

fig.update_layout(legend_orientation="h")

fig.show()
```

Crimes Over the Years in Baltimoe by Type



The graph Crimes in Baltimore by Type showcase the magnitude of type of crimes over the years, we note that carjacking,commercial robbery, rape, arson and shooting are around the same magnitude and seem to follow the same trend. On the other hand, autoteft and robbery also seem to follow the same trend. Larceny, has decreased since 2013 while Burglary has decreased since 2016.

In [86]:

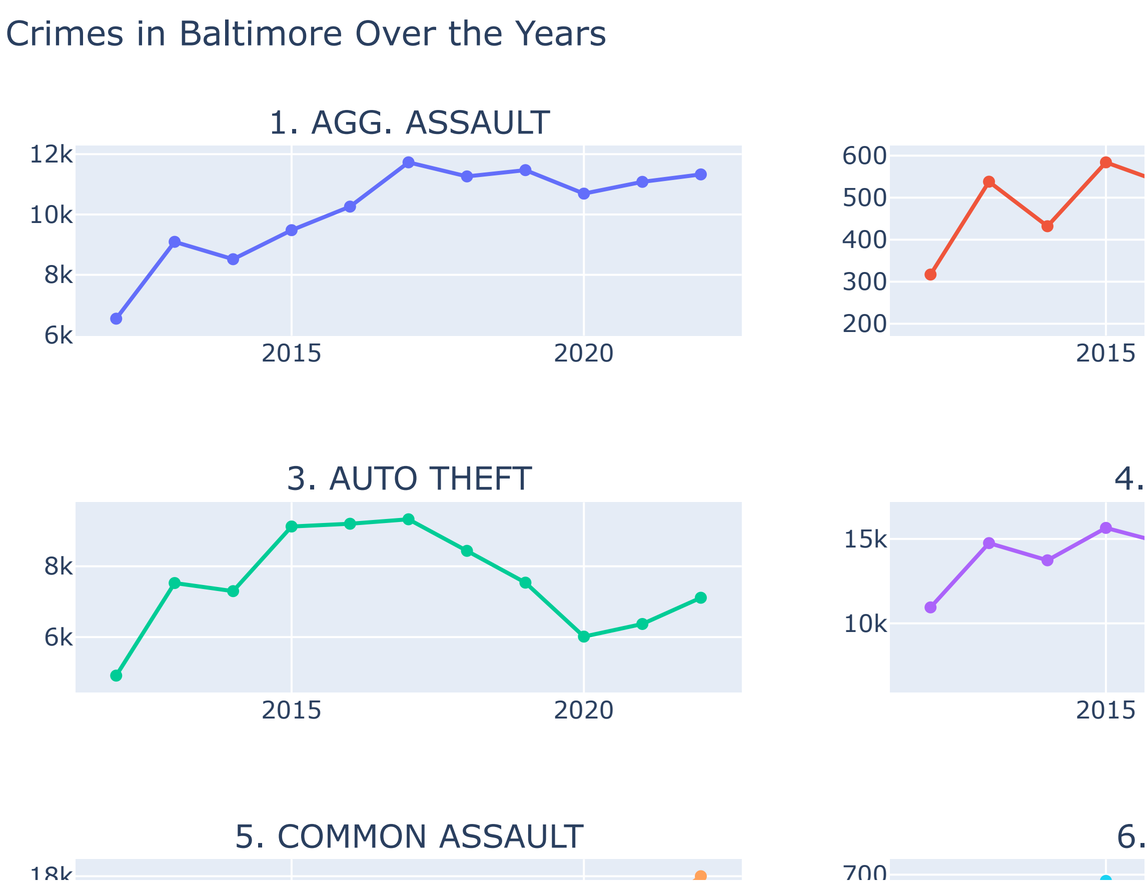
```
from plotly.subplots import make_subplots

fig = make_subplots(
    rows=7, cols=2,
    subplot_titles=[str(i+1) + ". " + crime_types[i] for i in range(len(crime_types))
)
```

In [87]:

```
# function to update row and col for adding subplots
current_row = 1
current_col = 1
def update_row_col(current_row, current_col):
    if current_col < 2:
        current_col += 1
    else:
        current_col = 1
        current_row += 1
    return current_row, current_col
```

In [88]:

```
years=sorted(df_crime["year"].unique())

# add trace to the subplot
#fig = go.Figure()
current_count = 1
for current_crime in crime_types:
    current_type_count = crime_count_by_year[current_crime]
    fig.add_trace(
        go.Scatter(
            x=year_labels,
            y=current_type_count,
            mode='lines+markers',
            name=current_crime
        ),
        row=current_row, col=current_col

    )

    current_row, current_col = update_row_col(current_row, current_col)

fig.update_layout(
    height=1500,
    width=900,
    title_text="Crimes in Baltimore Over the Years"
)

fig.update_layout(legend_orientation="h")
fig.show()
```



If we look at the type of crime over the years individually we can see that carjacking increased in 2013. Shooting increased sharply from 2012 to 2015, then from 2015 it steadily goes up. Robbery and rape both reached a peak in 2017. Just like we noticed in the lacercy clearly sees a decline since 2013 and burglary has decreased since 2017 going down. Larceny and Larceny from auto both show a downward trend. Aggregated assault and homicide also seems to follow the same upward trend we noticed in the aggregated graph.

.

We started our analysis in 2012, however, I suspect that year 2012 might be incomplete. In the next analysis I'm taking the first year as baseline, because I don't want to risk a bias, I am removing 2012 and keeping 2013 as the baseline. We will be able to see how much a type of crime in given year has increased % wise since 2013.

In [89]:

```
baseline_year = crime_count_by_year.iloc[1,1:]#taking year 2013 here
crime_count_by_year_percent_change = 100 * round((crime_count_by_year.iloc[1:,1:] - b
crime_count_by_year_percent_change["year"] = year_labels[1:]
crime_count_by_year_percent_change
```

Out[89]:

	AGG. ASSAULT	ARSON	AUTO THEFT	BURGLARY	COMMON ASSAULT	HOMICIDE	LARCENY	LARCENY FROM AUTO	RAPE	ROBE
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	-6.0	-20.0	-3.0	-7.0	-11.0	-9.0	-7.0	0.0	-10.0	-
3	4.0	9.0	21.0	6.0	-16.0	48.0	-13.0	5.0	5.0	
4	13.0	-1.0	22.0	-0.0	-10.0	37.0	-14.0	-3.0	8.0	
5	29.0	-1.0	24.0	10.0	6.0	48.0	-11.0	-8.0	39.0	
6	24.0	-53.0	12.0	-16.0	1.0	33.0	-12.0	-5.0	34.0	
7	26.0	-57.0	0.0	-26.0	1.0	50.0	-11.0	-14.0	16.0	
8	18.0	-61.0	-20.0	-45.0	-10.0	45.0	-37.0	-45.0	7.0	-
9	22.0	-48.0	-15.0	-53.0	-1.0	44.0	-41.0	-32.0	7.0	-
10	25.0	-56.0	-6.0	-50.0	8.0	43.0	-32.0	-48.0	-17.0	-

The results above clearly show that Larceny, Larceny auto and Arson have declining from 2013. Shooting has skyrocket if we compared to 2013, while ROBBERY - CARJACKING has also increased.

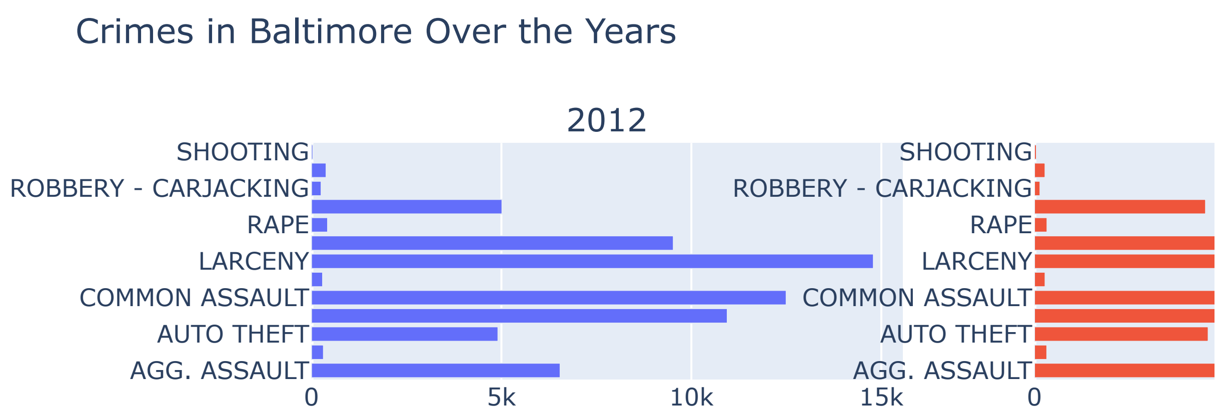
In [90]:

```
fig = make_subplots(
    rows=6, cols=2,
    subplot_titles=[str(i) for i in year_labels]
)
```

In [91]:

```
# function to update row and col for adding subplots
current_row = 1
current_col = 1
def update_row_col(current_row, current_col):
    if current_col < 2:
        current_col += 1
    else:
        current_col = 1
        current_row += 1
    return current_row, current_col
```

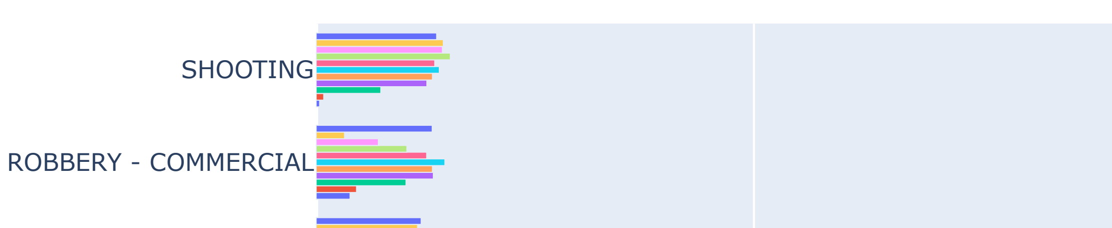
In [92]:
```
#df_crime['Description'].value_counts()



years=sorted(df_crime["year"].unique())

#df_crime[df_crime['year']==years[1]]



# add trace to the subplot
current_count = 1
for i in range(len(years)):
    a= df_crime[df_crime['year']==years[i]]
    b=a.groupby(["Description"]).size().reset_index(name='counts')
    y_counts=b['counts']
    x_des=b['Description']
    fig.add_trace(
        go.Bar(
            y=x_des,
            x=y_counts,
             orientation='h',
            name=str(years[i])


        ),
        row=current_row, col=current_col,
    )
    current_row, current_col = update_row_col(current_row, current_col)

fig.update_layout(
    height=1500,
    width=900,
    title_text="Crimes in Baltimore Over the Years",

)

fig.update_layout(legend_orientation="h")
fig.show()
```



In [93]:

```
fig = go.Figure()



for i in range(len(years)):
    a= df_crime[df_crime['year']==years[i]]
    b=a.groupby(["Description"]).size().reset_index(name='counts')
    bs=b['counts']
    fig.add_trace(
        go.Bar(
            x=bs,
            y=b['Description'],
            orientation='h',
            name=str(years[i])
        )
    )
# Edit the layout
fig.update_layout(title='Crimes Over the Years in Baltimoe by Type',
                    xaxis_title='Year',
                    yaxis_title='Absolute Change',
                    autosize=True,
                    height=800
                 )

fig.update_layout(legend_orientation="h")

fig.show()
```

Crimes Over the Years in Baltimoe by Type



The 2 previous bar chart (individual and aggregate) analysis show us that 2022 compared to other years has two of highest numbers of most violent crimes (common assault, aggregate assault). 2013 is interesting because we can see how the other type of crimes are lower compared to other years except for Larceny which is the highest for that year.

In [94]:

```
# Group the data by year and hour, and count the number of crimes for each group
crime_by_hour_year = df_crime.groupby(['hour', 'year']).size().reset_index(name='cour

# For each year, find the hour with the maximum count of crimes
crime_by_hour_year_max = crime_by_hour_year.groupby('year')['counts'].idxmax()
crime_peak_hour_year = crime_by_hour_year.loc[crime_by_hour_year_max]

# Display the result
crime_peak_hour_year
```

Out[94]:

	hour	year	counts
198	18	2012	4071

	hour	year	counts
166	15	2013	5836
167	15	2014	5516
201	18	2015	5870
202	18	2016	5962
5	0	2017	6667
204	18	2018	5768
7	0	2019	5468
8	0	2020	4498
9	0	2021	4289

The table above shows the time when the highest number of crimes happen per year. I notice here that between 2012 and 2016 the highest number of crimes happened between 15h and 18h, year 2018 and year 2022 highest number are respectively 18h and 17h. On the other hand, the highest number of crimes in 2018, and 2019 to 2021 happened at midnight. I can conclude here that there is no real pattern except for the fact that the highest number of crimes do not happen in the middle of the night or in the morning.

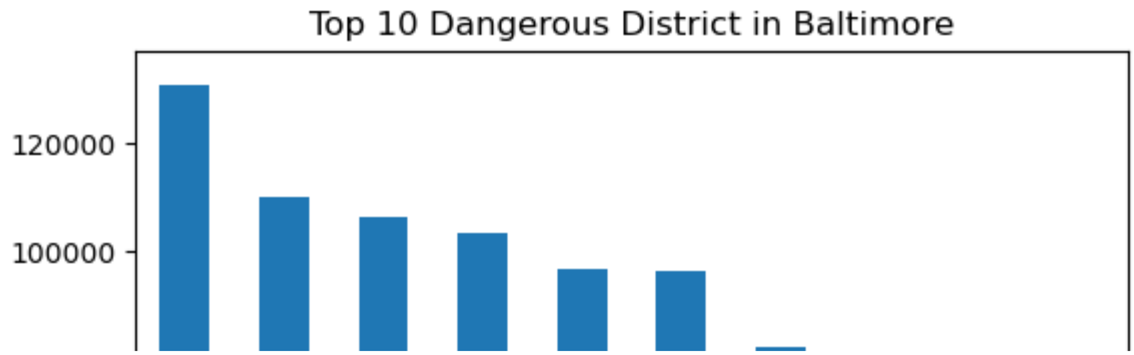
Crime by District

In [95]:

```
df_crime["District"].value_counts()[1:11].plot.bar(
    title='Top 10 Dangerous District in Baltimore')
nameplot.set_xlabel('block name',size=20)
nameplot.set_ylabel('count',size=20)
```

Out[95]:

```
Text(38.0, 0.5, 'count')
```



In [96]:

```
df_crime["Neighborhood"].value_counts()[1:11].plot.bar(
    title='Top 10 Dangerous Neighborhood in Baltimore')
nameplot.set_xlabel('block name',size=20)
nameplot.set_ylabel('count',size=20)
```

Out[96]:

```
Text(38.0, 0.5, 'count')
```

Top 10 Dangerous Neighborhood in Baltimore

In the above results we see that the value that appears the most in the most dangerous neighbourhood is N/A, this even though only 2% of the missing values in the column. The second value that is the neighborhood of Frankford. This makes sense since Frankford,according to Wikipedia, is the most populous of the city's designated neighborhoods, with over 17,000 residents. Frankford is a neighborhood in northeast Baltimore. According to our results, the NorthEast district is the 4th most dangerous district, therefore, the only reason why Frankford is has the highest number of crimes is because is densily populated and not because it stands on a particularly dangerous district. In fact, the most dangerous district according to our data is southeastern district.

In [97]:

```
###95% of ethinicity is missing, while around 2% of race is missing
##this means that ethinicity was not filled in most of the time
##Also after analysing the data I noticed that ethnicity sometimes doesn't match the
##I will proceed to two different analysis, one condisering the ethnicity and race ar
```

Heatmap Analysis

The data provides us with Latitude and longitude, with this, we can create a heatmap. Before creating the map however, we need to remove all the erreneous records. This includes 0's and the 99 values that we added to replace the NUll values.

In [98]:

```
import folium
from folium.plugins import HeatMap

# Remove rows with missing Latitude or Longitude
df_heatmap = df_crime.dropna(subset=['Latitude', 'Longitude'])
df_heatmap= df_heatmap.drop(df_heatmap[df_heatmap['Longitude']==99].index)
df_heatmap= df_heatmap.drop(df_heatmap[df_heatmap['Latitude']==99].index)
```

In [99]:

```
#checking if we have Longitude and Latitude as 0's
df_crime[df_crime['Longitude']==0]
```

Out[99]:

	RowID	CCNO	CrimeDateTime	CrimeCode	Location	Description	Inside_Outside
11410	11411	22L06729	2022-12-22 07:35:00	6D	LOMBARD ST & S EAST AV	LARCENY FROM AUTO	N/A
12252	12253	22L06435	2022-12-21 10:00:00	3AF	ST & COLVIN ST	ROBBERY	N/A
13952	13953	22L05426	2022-12-18 00:30:00	4E	ST & S WOLFE ST	COMMON ASSAULT	N/A
13962	13963	22L05426	2022-12-18 00:30:00	4E	ST & S WOLFE ST	COMMON ASSAULT	N/A

	RowID	CCNO	CrimeDateTime	CrimeCode	Location	Description	Inside_Outside
16697	16698	22L04124	2022-12-13 16:30:00	6G	900 ELLICOTT DY	LARCENY	N/A
...	...	...	...	...	...	...	...
1048470	1048471	12H11824	2012-08-24 10:35:00	6F	800 W MADISON ST	LARCENY	O
1048502	1048503	12H02762	2012-08-06 08:00:00	6E	ST & EUTAW PL	LARCENY	O
1048527	1048528	12I02042	2012-09-04 15:00:00	5D	200 HAWTHORNE RD	BURGLARY	I
1048564	1048565	12H07745	2012-08-15 18:00:00	6E	6400 E PRATT ST	LARCENY	O
1048572	1048573	12H11988	2012-08-24 16:10:00	6J	SARATOGA ST & N MLK JR BD	LARCENY	O

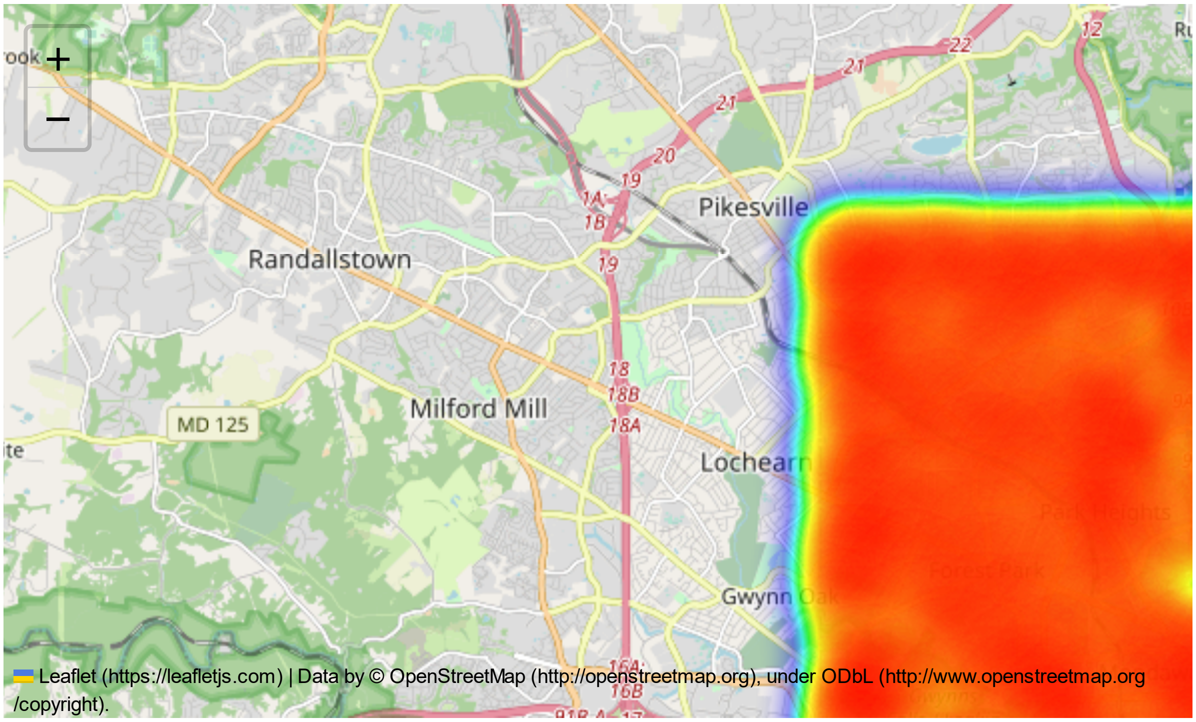
In [100…

```
#we can see that some rows are filled with erroneaous information so we should remove
#once again

df_heatmap= df_heatmap.drop(df_heatmap[df_heatmap['Latitude']==0.000000].index)
df_heatmap= df_heatmap.drop(df_heatmap[df_heatmap['Longitude']==0.000000].index)
```

In [101…

```
# Create a map centered around Baltimore
m = folium.Map(location=[39.2904, -76.6122], zoom_start=12)

heat_map = df_heatmap[['Latitude','Longitude']].to_numpy()
#HeatMap(wv_mat).add_to(heat_m)


HeatMap(heat_map).add_to(m)

m
```

Out[101…



The heatmap does not provide any interesting information, what we notice is that the data is distributed evenly whithin Baltimore.

In [102…

```
# Group the data by latitude and longitude and count the number of crimes for each gr
crime_by_location = df_heatmap.groupby(['Latitude', 'Longitude']).size().reset_index(

crime_by_location
```

Out[102…

	Latitude	Longitude	counts
0	39.200434	-76.553318	1
1	39.200741	-76.555502	50
2	39.200749	-76.555504	10
3	39.200820	-76.555785	4
4	39.201917	-76.556505	10
...	...	...	...
143325	39.371975	-76.590354	6
143326	39.371976	-76.589385	4
143327	39.371977	-76.589507	2
143328	39.371979	-76.564571	2
143329	39.371981	-76.589688	2

143330 rows × 3 columns

In [103…

```
# Filter out placeholder coordinates
#crime_by_location = crime_by_location[(crime_by_location['Latitude'] != 0) & (crime_

# Find the location with the maximum count of crimes
most_dense_location = crime_by_location.loc[crime_by_location['counts'].idxmax()]
most_dense_location
```

Out[103…

```
Latitude        39.318685
Longitude      -76.654398
counts        1582.000000
Name: 89085, dtype: float64
```

In [104…

```
lat_range = (most_dense_location['Latitude'] - 0.01, most_dense_location['Latitude']
print(lat_range)
lon_range = (most_dense_location['Longitude'] - 0.01, most_dense_location['Longitude
lon_range
```

```
(39.30868504, 39.328685039999996)
```

Out[104…

```
(-76.66439769, -76.64439768999999)
```

In [105…

```
# Define a small range around the most dense location to consider as the 'zone'
lat_range = (most_dense_location['Latitude'] - 0.01, most_dense_location['Latitude']
lon_range = (most_dense_location['Longitude'] - 0.01, most_dense_location['Longitude

# Filter the data for crimes that occurred in this zone
df_zone = df_crime[(df_crime['Latitude'].between(*lat_range)) & (df_crime['Longitude

# Count the number of each type of crime in the zone
crime_counts = df_zone['Description'].value_counts()

# Get the top 3 types of crime
top_3_crimes = crime_counts.head(3)
top_3_crimes
```

Out[105…

```
LARCENY           5752
COMMON ASSAULT    4405
AGG. ASSAULT      3102
Name: Description, dtype: int64
```

From the above analysis we find that Larcency, common assault and Agg. Assault are the 3 most common crimes around the most dense crime location.

Predictive Modeling: Linear Regression

Here below I'm taking a simple predictive model - a regression model per type of crime. For this, I need to convert the data into a pivot table. In this case I took year as the dependant value and #of crimes for a specific crime as the independant value. Because of the data way the data is presented I can't do a mutiple regression model.

In [106…

```
crime_by_year_type = df_crime.groupby(['year', 'Description']).size().reset_index(nar

pivot_data = crime_by_year_type.pivot(index='year', columns='Description', values='co
pivot_data
```

Out[106…

Description	AGG. ASSAULT	ARSON	AUTO THEFT	BURGLARY	COMMON ASSAULT	HOMICIDE	LARCENY	LARCENY FROM AUTO	RAI
year									
2012	6547	317	4911	10946	12497	295	14792	9526	42
2013	9094	538	7527	14754	16705	463	24338	13384	54
2014	8518	432	7298	13734	14906	422	22674	13432	49
2015	9480	584	9124	15654	13968	684	21280	14094	57
2016	10262	534	9202	14740	14994	636	20832	13030	59
2017	11728	532	9328	16164	17638	684	21608	12372	76
2018	11262	254	8436	12436	16896	618	21422	12754	73
2019	11470	230	7538	10854	16830	696	21546	11556	63
2020	10692	212	6014	8112	14994	670	15348	7324	58
2021	11082	278	6370	6904	16458	668	14439	9161	58
2022	11328	238	7111	7429	18000	660	16580	6984	45

In [107…

```
from sklearn.linear_model import LinearRegression

# Group the data by year and description, and count the number of crimes for each gro
crime_by_year_type = df_crime.groupby(['year', 'Description']).size().reset_index(nar

# Pivot the data to have years as rows and crime types as columns
pivot_data = crime_by_year_type.pivot(index='year', columns='Description', values='co

# Create a linear regression model for each crime type
models = {}
for crime_type in pivot_data.columns:
    X = pivot_data.index.values.reshape(-1, 1)  # Features (years)
    y = pivot_data[crime_type].values  # Target (counts)
    model = LinearRegression().fit(X, y)
    models[crime_type] = model

# Predict the amount of each crime type for 2023
predictions = {crime_type: model.predict([[2023]])[0] for crime_type, model in models
predictions
```

Out[107…

```
{'AGG. ASSAULT': 12498.03636363626,
 'ARSON': 209.0181818181809,
 'AUTO THEFT': 7455.290909090909,
 'BURGLARY': 7734.0,
 'COMMON ASSAULT': 17685.109090909245,
 'HOMICIDE': 775.7272727272721,
```

```
 'LARCENY': 16722.89090909087,
 'LARCENY FROM AUTO': 8331.836363636306,
 'RAPE': 623.9090909090919,
 'ROBBERY': 6939.927272727276,
 'ROBBERY - CARJACKING': 1455.9272727272764,
 'ROBBERY - COMMERCIAL': 1107.4000000000015,
 'SHOOTING': 1900.9818181818118}
```

In [122…

```
prediction= pd.DataFrame(predictions.items(), columns=['Date', 'count_prediction'])
```

In [127…

```
crime_2013=df_crime2013.groupby(['year', 'Description']).size().reset_index(name='cou

crime_2013['counts12']= crime_2013['counts']*2

crime_2013['prediction']= round(prediction['count_prediction'])

crime_2013['difference']=round((crime_2013['prediction']-crime_2013['counts12'])/crir
crime_2013
```

Out[127…

	year	Description	counts	counts12	prediction	difference
0	2023	AGG. ASSAULT	3989	7978	12498.0	57.0
1	2023	ARSON	90	180	209.0	16.0
2	2023	AUTO THEFT	5436	10872	7455.0	-31.0
3	2023	BURGLARY	2215	4430	7734.0	75.0
4	2023	COMMON ASSAULT	7613	15226	17685.0	16.0
5	2023	HOMICIDE	220	440	776.0	76.0
6	2023	LARCENY	7073	14146	16723.0	18.0
7	2023	LARCENY FROM AUTO	2917	5834	8332.0	43.0
8	2023	RAPE	195	390	624.0	60.0
9	2023	ROBBERY	2288	4576	6940.0	52.0
10	2023	ROBBERY - CARJACKING	370	740	1456.0	97.0
11	2023	ROBBERY - COMMERCIAL	369	738	1107.0	50.0
12	2023	SHOOTING	477	954	1901.0	99.0

The dataset contains 6 months of 2023 data while the prediction is for the full year of 2023. To compare both I simply divide the prediction by two and then calculate the difference between one and the other. The table above shows that the prediction is off.

Chi-Square Test of Independence

Here below I'm trying to answer two different questions: Does race have an impact on the type of crime? Does Age and Gender has an impact on the type of crime?

Here I'm using chi2_contingency - the chi2 -contingency- is used when we don't know the underlying distribution but you want to test whether two (or more) groups have the same distribution. The null hypothesis is: two groups have no significant difference.

In [109…

```
df_crime['Race'].unique()
```

Out[109…

```
array(['BLACK_OR_AFRICAN_AMERICAN', 'N/A', 'WHITE', 'ASIAN', 'UNKNOWN',
       'AMERICAN_INDIAN_OR_ALASKA_NATIVE',
       'NATIVE_HAWAIIAN_OR_OTHER_PACIFIC_ISLANDER'], dtype=object)
```

In [110…

```
df_crime=df_crime.drop(df_crime[df_crime['Race']=='N/A'].index)
df_crime=df_crime.drop(df_crime[df_crime['Race']=='UNKNOWN'].index)
```

In [111…

```
from scipy.stats import chi2_contingency

# Group the data by race and description, and count the number of crimes for each gro
crime_by_race_type = df_crime.groupby(['Race', 'Description']).size().reset_index(nar

# Pivot the data to have races as rows and crime types as columns
pivot_data = crime_by_race_type.pivot(index='Race', columns='Description', values='co

# Perform a chi-square test of independence
chi2, p, dof, expected = chi2_contingency(pivot_data)
chi2, p
```

Out[111…

```
(36567.05732968939, 0.0)
```

In [112…

```
# Create age groups
bins = [0, 25, 45, np.inf]
AgeGroup = ['<25', '25-45', '45+']

# Add column using np.where()
def f(x):
    if (x < 25):
        return '<25'
    elif (25 <= x < 45):
        return '45+'
    elif (x>=45):
        return '25-45'
```

In [113…

```
df_crime['AgeGroup'] = df_crime['Age'].apply(f)
df_crime
```

Out[113…

	RowID	CCNO	CrimeDateTime	CrimeCode	Location	Description	Inside_Outside
8884	8885	22L08161	2022-12-27 19:50:00	4B	2800 BELMONT AVE	AGG. ASSAULT	N/A

	RowID	CCNO	CrimeDateTime	CrimeCode	Location	Description	Inside_Outside
8885	8886	22L08175	2022-12-27 19:03:00	4E	5600 MAYVIEW AVE	COMMON ASSAULT	N/A
8886	8887	22L08176	2022-12-27 19:55:00	4B	1900 BAKER ST	AGG. ASSAULT	N/A
8887	8888	22L08177	2022-12-27 20:00:00	6F	2400 FREDERICK AVE	LARCENY	N/A
8888	8889	22L08182	2022-12-27 19:30:00	6D	4300 PARKTON ST	LARCENY FROM AUTO	N/A
...	...	...	...	...	...	...	...
1048567	1048568	12H11776	2012-08-24 02:30:00	7A	1100 CLOVERDALE RD	AUTO THEFT	O
1048568	1048569	12H13628	2012-08-24 12:00:00	6G	1500 S CLINTON ST	LARCENY	I
1048570	1048571	12H12047	2012-08-24 08:30:00	7A	1300 N KENWOOD AVE	AUTO THEFT	O
1048573	1048574	12H12854	2012-08-24 11:00:00	7A	2000 E FAYETTE ST	AUTO THEFT	O
1048574	1048575	12H12088	2012-08-24	4C	5600 BELAIR	AGG.	O

In [114…

```
# Group the data by AgeGroup and description, and count the number of crimes for each
crime_by_AgeGroup = df_crime.groupby(['AgeGroup', 'Description']).size().reset_index(

# Pivot the data to have races as rows and crime types as columns
pivot_dataA = crime_by_AgeGroup.pivot(index='AgeGroup', columns='Description', values

# Perform a chi-square test of independence
chi2, p, dof, expected = chi2_contingency(pivot_dataA)
chi2, p
```

Out[114…

```
(61875.689900384226, 0.0)
```

In [115…

```
df_crime=df_crime.drop(df_crime[df_crime['Gender']=='N/A'].index)
```

In [116…

```
# Group the data by Gender and description, and count the number of crimes for each g

crime_by_Gender = df_crime.groupby(['Gender', 'Description']).size().reset_index(name

# Pivot the data to have races as rows and crime types as columns
pivot_dataG = crime_by_Gender.pivot(index='Gender', columns='Description', values='co

# Perform a chi-square test of independence
chi2, p, dof, expected = chi2_contingency(pivot_dataG)
chi2, p
```

Out[116…

```
(729994.1979187021, 0.0)
```

We reject the null hypothesis in the 3 cases, meaning that there is a difference in the outcome regarding age group , gender and race.

Conclusion

Baltimore dataset contains data starting from the 1960's, however the entries don't seem consistent (only a few in a total of half a million). The Data becomes more consistent from year 2012, however data is incomplete for 2023 (since the year isn't finished). Therefore the analysis is from 2012 to 2013.

Baltimore crime data shows that specific types of crimes are more 'popular' regardless of the year, namely Larceny, Common Assault and Burglary. While others are less 'popular' regardless of the year, namely Homicide, Rape and Arson. Larceny and Larceny from auto both show a downward trend. Aggregated assault and homicide seem to follow the same upward trend. Robbery and rape both reached a peak in 2017. Shooting increased sharply from 2012 to 2015, then from 2015 it steadily goes up.

Frankford is the city with the highest crime level while the district with the highest level of crime is southeast. However, when we look at the heatmap, no particular city or district stands out. From the above analysis we find that Larcency, common assault and Agg. Assault are the 3 most common crimes around the most dense crime location (based on latitude and longitude).

When it comes to the average time when crimes where pertpetuated, we see that it varies depending on the year. The only pattern noticeable is that crimes tend to happen between the afternoon (from 15h) to midnight.

I performed a simple regression with the years as the dependent value and number of crimes per type of crime as the independant value. I then predicted the number of crimes for 2023 and compared the results with the 2023 data we had previously (by doubling the number of crimes for 2023). I concluded that the results are off, and that a deeper analysis should be done if we want to forecast the number of crimes (ex.: use of time series).

I also checked if race, age or gender has an impact on the type of crime by performing a chi2_contigency test and concluded it does. Further analysis would need to be done to see what are exactly the differences

In [4]:

```
pip install nbconvert
```

```
Requirement already satisfied: nbconvert in c:\users\15147\anaconda3\lib\site-package
s (6.1.0)Note: you may need to restart the kernel to use updated packages.

Requirement already satisfied: jupyterlab-pygments in c:\users\15147\anaconda3\lib\si
te-packages (from nbconvert) (0.1.2)
Requirement already satisfied: nbformat>=4.4 in c:\users\15147\anaconda3\lib\site-pac
kages (from nbconvert) (5.1.3)
Requirement already satisfied: jupyter-core in c:\users\15147\anaconda3\lib\site-pack
ages (from nbconvert) (4.8.1)
Requirement already satisfied: entrypoints>=0.2.2 in c:\users\15147\anaconda3\lib\sit
e-packages (from nbconvert) (0.3)
Requirement already satisfied: pygments>=2.4.1 in c:\users\15147\anaconda3\lib\site-p
ackages (from nbconvert) (2.10.0)
Requirement already satisfied: traitlets>=5.0 in c:\users\15147\anaconda3\lib\site-pa
ckages (from nbconvert) (5.1.0)
Requirement already satisfied: nbclient<0.6.0,>=0.5.0 in c:\users\15147\anaconda3\li
b\site-packages (from nbconvert) (0.5.3)
Requirement already satisfied: bleach in c:\users\15147\anaconda3\lib\site-packages
(from nbconvert) (4.0.0)
Requirement already satisfied: mistune<2,>=0.8.1 in c:\users\15147\anaconda3\lib\site
-packages (from nbconvert) (0.8.4)
Requirement already satisfied: pandocfilters>=1.4.1 in c:\users\15147\anaconda3\lib\s
ite-packages (from nbconvert) (1.4.3)
Requirement already satisfied: defusedxml in c:\users\15147\anaconda3\lib\site-packag
es (from nbconvert) (0.7.1)
Requirement already satisfied: testpath in c:\users\15147\anaconda3\lib\site-packages
(from nbconvert) (0.5.0)
Requirement already satisfied: jinja2>=2.4 in c:\users\15147\anaconda3\lib\site-packa
ges (from nbconvert) (2.11.3)
Requirement already satisfied: MarkupSafe>=0.23 in c:\users\15147\anaconda3\lib\site-
packages (from jinja2>=2.4->nbconvert) (1.1.1)
Requirement already satisfied: nest-asyncio in c:\users\15147\anaconda3\lib\site-pack
ages (from nbclient<0.6.0,>=0.5.0->nbconvert) (1.5.1)
Requirement already satisfied: async-generator in c:\users\15147\anaconda3\lib\site-p
ackages (from nbclient<0.6.0,>=0.5.0->nbconvert) (1.10)
Requirement already satisfied: jupyter-client>=6.1.5 in c:\users\15147\anaconda3\lib\
site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert) (6.1.12)
Requirement already satisfied: pyzmq>=13 in c:\users\15147\anaconda3\lib\site-package
s (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (22.2.1)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\15147\anaconda3\lib\s
ite-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (2.8.2)
Requirement already satisfied: tornado>=4.1 in c:\users\15147\anaconda3\lib\site-pack
ages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert) (6.1)
Requirement already satisfied: pywin32>=1.0 in c:\users\15147\anaconda3\lib\site-pack
ages (from jupyter-core->nbconvert) (228)
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in c:\users\15147\anaconda3\li
b\site-packages (from nbformat>=4.4->nbconvert) (3.2.0)
Requirement already satisfied: ipython-genutils in c:\users\15147\anaconda3\lib\site-
packages (from nbformat>=4.4->nbconvert) (0.2.0)
Requirement already satisfied: six>=1.11.0 in c:\users\15147\anaconda3\lib\site-packa
ges (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert) (1.16.0)
Requirement already satisfied: setuptools in c:\users\15147\anaconda3\lib\site-packag
```

```
es (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert) (58.0.4)
Requirement already satisfied: pyrsistent>=0.14.0 in c:\users\15147\anaconda3\lib\sit
e-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert) (0.18.0)
Requirement already satisfied: attrs>=17.4.0 in c:\users\15147\anaconda3\lib\site-pac
kages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert) (21.2.0)
Requirement already satisfied: packaging in c:\users\15147\anaconda3\lib\site-package
s (from bleach->nbconvert) (23.1)
Requirement already satisfied: webencodings in c:\users\15147\anaconda3\lib\site-pack
```

In [6]:

```
pip install nbconvert[webpdf]
```

```
Requirement already satisfied: nbconvert[webpdf] in c:\users\15147\anaconda3\lib\site
-packages (6.1.0)
Requirement already satisfied: mistune<2,>=0.8.1 in c:\users\15147\anaconda3\lib\site
-packages (from nbconvert[webpdf]) (0.8.4)
Requirement already satisfied: entrypoints>=0.2.2 in c:\users\15147\anaconda3\lib\sit
e-packages (from nbconvert[webpdf]) (0.3)
Requirement already satisfied: jinja2>=2.4 in c:\users\15147\anaconda3\lib\site-packa
ges (from nbconvert[webpdf]) (2.11.3)
Requirement already satisfied: pandocfilters>=1.4.1 in c:\users\15147\anaconda3\lib\s
ite-packages (from nbconvert[webpdf]) (1.4.3)
Requirement already satisfied: nbclient<0.6.0,>=0.5.0 in c:\users\15147\anaconda3\li
b\site-packages (from nbconvert[webpdf]) (0.5.3)
Requirement already satisfied: jupyter-core in c:\users\15147\anaconda3\lib\site-pack
ages (from nbconvert[webpdf]) (4.8.1)
Requirement already satisfied: jupyterlab-pygments in c:\users\15147\anaconda3\lib\si
te-packages (from nbconvert[webpdf]) (0.1.2)
Requirement already satisfied: nbformat>=4.4 in c:\users\15147\anaconda3\lib\site-pac
kages (from nbconvert[webpdf]) (5.1.3)
Requirement already satisfied: defusedxml in c:\users\15147\anaconda3\lib\site-packag
es (from nbconvert[webpdf]) (0.7.1)
Requirement already satisfied: bleach in c:\users\15147\anaconda3\lib\site-packages
(from nbconvert[webpdf]) (4.0.0)
Requirement already satisfied: testpath in c:\users\15147\anaconda3\lib\site-packages
(from nbconvert[webpdf]) (0.5.0)
Requirement already satisfied: traitlets>=5.0 in c:\users\15147\anaconda3\lib\site-pa
ckages (from nbconvert[webpdf]) (5.1.0)
Requirement already satisfied: pygments>=2.4.1 in c:\users\15147\anaconda3\lib\site-p
ackages (from nbconvert[webpdf]) (2.10.0)
Collecting pyppeteer==0.2.2
  Downloading pyppeteer-0.2.2-py3-none-any.whl (145 kB)
Requirement already satisfied: appdirs<2.0.0,>=1.4.3 in c:\users\15147\anaconda3\lib\
site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (1.4.4)
Collecting websockets<9.0,>=8.1
  Downloading websockets-8.1.tar.gz (58 kB)
Requirement already satisfied: urllib3<2.0.0,>=1.25.8 in c:\users\15147\anaconda3\li
b\site-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (1.26.7)
Collecting pyee<8.0.0,>=7.0.1
  Downloading pyee-7.0.4-py2.py3-none-any.whl (12 kB)
Requirement already satisfied: tqdm<5.0.0,>=4.42.1 in c:\users\15147\anaconda3\lib\si
te-packages (from pyppeteer==0.2.2->nbconvert[webpdf]) (4.62.3)
Requirement already satisfied: MarkupSafe>=0.23 in c:\users\15147\anaconda3\lib\site-
packages (from jinja2>=2.4->nbconvert[webpdf]) (1.1.1)
Requirement already satisfied: async-generator in c:\users\15147\anaconda3\lib\site-p
ackages (from nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (1.10)
Requirement already satisfied: nest-asyncio in c:\users\15147\anaconda3\lib\site-pack
ages (from nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (1.5.1)
Requirement already satisfied: jupyter-client>=6.1.5 in c:\users\15147\anaconda3\lib\
```

```
site-packages (from nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (6.1.12)
Requirement already satisfied: pyzmq>=13 in c:\users\15147\anaconda3\lib\site-package
s (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (22.2.1)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\15147\anaconda3\lib\s
ite-packages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert[webpdf])
(2.8.2)
Requirement already satisfied: tornado>=4.1 in c:\users\15147\anaconda3\lib\site-pack
ages (from jupyter-client>=6.1.5->nbclient<0.6.0,>=0.5.0->nbconvert[webpdf]) (6.1)
Requirement already satisfied: pywin32>=1.0 in c:\users\15147\anaconda3\lib\site-pack
ages (from jupyter-core->nbconvert[webpdf]) (228)
Requirement already satisfied: jsonschema!=2.5.0,>=2.4 in c:\users\15147\anaconda3\li
b\site-packages (from nbformat>=4.4->nbconvert[webpdf]) (3.2.0)
Requirement already satisfied: ipython-genutils in c:\users\15147\anaconda3\lib\site-
packages (from nbformat>=4.4->nbconvert[webpdf]) (0.2.0)
Requirement already satisfied: attrs>=17.4.0 in c:\users\15147\anaconda3\lib\site-pac
kages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert[webpdf]) (21.2.0)
Requirement already satisfied: six>=1.11.0 in c:\users\15147\anaconda3\lib\site-packa
ges (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert[webpdf]) (1.16.0)
Requirement already satisfied: pyrsistent>=0.14.0 in c:\users\15147\anaconda3\lib\sit
e-packages (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert[webpdf]) (0.18.0)
Requirement already satisfied: setuptools in c:\users\15147\anaconda3\lib\site-packag
es (from jsonschema!=2.5.0,>=2.4->nbformat>=4.4->nbconvert[webpdf]) (58.0.4)
Requirement already satisfied: colorama in c:\users\15147\anaconda3\lib\site-packages
(from tqdm<5.0.0,>=4.42.1->pyppeteer==0.2.2->nbconvert[webpdf]) (0.4.4)
Requirement already satisfied: packaging in c:\users\15147\anaconda3\lib\site-package
s (from bleach->nbconvert[webpdf]) (23.1)
Requirement already satisfied: webencodings in c:\users\15147\anaconda3\lib\site-pack
ages (from bleach->nbconvert[webpdf]) (0.5.1)
Building wheels for collected packages: websockets
  Building wheel for websockets (setup.py): started
  Building wheel for websockets (setup.py): finished with status 'done'
  Created wheel for websockets: filename=websockets-8.1-cp39-cp39-win_amd64.whl size=
62758 sha256=dbbf24eec2d77cb4243333c37a18849267b6522232780054af6a7cefc86b5e44
  Stored in directory: c:\users\15147\appdata\local\pip\cache\wheels\d8\b9\a0\b97b211
aeda2ebd6ac2e43fc300d308dbf1f9df520ed390cae
Successfully built websockets
Installing collected packages: websockets, pyee, pyppeteer
Successfully installed pyee-7.0.4 pyppeteer-0.2.2 websockets-8.1
Note: you may need to restart the kernel to use updated packages.
```

In [ ]: