## Boston crime analysis

The goal of this study is to get an improved understanding of the offences that happen in Boston in order to enhance the policing strategy. We are going to answer the following questions:

- · What are the times and days are most affected by crime in Boston?
- What are the most frequent crimes in Boston?
- 🛘 Visualize using a map the amount of crimes depending their locations.

In order to do this, we will use the following dataset made from governmental data.

Let's first import all the packages that we will need for this study.

```
In [16]: from folium.plugins import HeatMap
from sklearn.cluster import KMeans

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

import warnings
%matplotlib inline
warnings.filterwarnings("ignore", category=FutureWarning)
```

### 0. Dataset preparation

Let's firstly take a look at our dataset in order to identify and organize the data that will help us in this study.

```
In [17]: # Load the dataset from the previously downloaded file
df = pd.read_csv("../data/boston_crimes_2016_02.csv")

# Show the first rows to have an idea of what the data looks like
df.head(3)
```

ut[17]:		Object	District	Date	Day	Hour	Latitude	Longitude
	0	Fraud	D4	2016-02-01 08:00:00	Monday	8	42.337403	-71.082215
	1	Fraud	В3	2016-02-01 00:00:00	Monday	0	42.296063	-71.086648
	2	Fraud	C11	2016-02-02 11:00:00	Tuesday	11	42.306480	-71.066758

```
In [18]: df.shape
Out[18]: (6803, 7)
```

There are not much columns and they all might help us in this study, we won't remove any of them for now. What could help us when drawing our next graphs whould be settings the Day column as categorical for keeping an order.

```
In [19]: df["Day"] = pd.Categorical(df["Day"], ["Monday", "Tuesday", "Wednesday", "Thursday", "Friday", "Saturday", "Sunday", "Sunday", "Golden and the standard and the st
```

```
'Harassment', 'Counterfeiting', 'Other',
                   'Police Service Incidents', 'Confidence Games', 'Larceny',
                   'Warrant Arrests', 'Vandalism', 'Missing Person Located',
                    'Motor Vehicle Accident Response', 'Auto Theft',
                    'Residential Burglary', 'Investigate Property', 'Robbery',
                   'Embezzlement', 'Restraining Order Violations',
                   'Disorderly Conduct', 'Landlord/Tenant Disputes', 'Medical Assistance', 'License Plate Related Incidents',
                   'Violations', 'Towed', 'Property Found', 'Aggravated Assault', 'Firearm Discovery', 'Liquor Violation', 'Simple Assault',
                   'Property Related Damage', 'Verbal Disputes', 'Firearm Violations', 'Fire Related Reports', 'Drug Violation', 'Evading Fare',
                    'Ballistics', 'Assembly or Gathering Violations',
                   'Auto Theft Recovery', 'License Violation',
                    'Operating Under the Influence', 'Bomb Hoax', 'Search Warrants',
                   'Harbor Related Incidents', 'Recovered Stolen Property', 'Prisoner Related Incidents', 'Commercial Burglary',
                   'Phone Call Complaints', 'Offenses Against Child / Family',
                    'Service', 'Manslaughter', 'Other Burglary', 'Arson',
                    'Prostitution', 'Homicide'], dtype=object)
```

△ Seeing the different values that are present in our Object column, it looks like our dataset is more of a "police intervention" dataset than a "crime dataset". Let's create a crime df that contains crime related interventions. For this, we will consider that objects in the following list are NOT crimes :

Property Lost, Investigate Person, Missing Person Located, Motor Vehicle Accident Response, Investigate Property, Medical Assistance, Property Found, Search Warrants, Recovered Stolen Property, Phone Call Complaints, Other

We are removing those items before working on our database.

```
In [25]: crime df = df.loc[~df["Object"].isin(["Property Lost", "Investigate Person", "Missing Person Located",
                                                "Motor Vehicle Accident Response", "Investigate Property", "Medical Assistance",
                                                "Property Found", "Search Warrants", "Recovered Stolen Property", "Phone Call Complaints", "Service", "Other"])].copy()
            crime_df["Object"].unique()
Out[25]: array(['Fraud', 'Missing Person Reported', 'Larceny From Motor Vehicle',
                     'Harassment', 'Counterfeiting', 'Police Service Incidents', 'Confidence Games', 'Larceny', 'Warrant Arrests', 'Vandalism', 'Auto Theft', 'Residential Burglary', 'Robbery', 'Embezzlement',
                     'Restraining Order Violations', 'Disorderly Conduct',
                      'Landlord/Tenant Disputes', 'License Plate Related Incidents',
                      'Violations', 'Towed', 'Aggravated Assault', 'Firearm Discovery',
                     'Liquor Violation', 'Simple Assault', 'Property Related Damage',
                     'Verbal Disputes', 'Firearm Violations', 'Fire Related Reports', 'Drug Violation', 'Evading Fare', 'Ballistics', 'Assembly or Gathering Violations', 'Auto Theft Recovery',
                     'License Violation', 'Operating Under the Influence', 'Bomb Hoax',
                     'Harbor Related Incidents', 'Prisoner Related Incidents',
                      'Commercial Burglary', 'Offenses Against Child / Family'
                      'Manslaughter', 'Other Burglary', 'Arson', 'Prostitution',
                     'Homicide'], dtype=object)
```

#### 

Let's check if there is any NaN or empty value in our dataset.

```
In [26]: # Check if there is any NaN value
         crime df[crime df.isna().any(axis=1)]
Out[26]: Object District Date Day Hour Latitude Longitude
In [27]: # Check if there is any null value
         crime df[crime df.isnull().any(axis=1)]
Out[27]:
          Object District Date Day Hour Latitude Longitude
In [28]: # Remove whitespaces in column names
         crime df.rename(columns=lambda x: x.strip(), inplace=True)
```

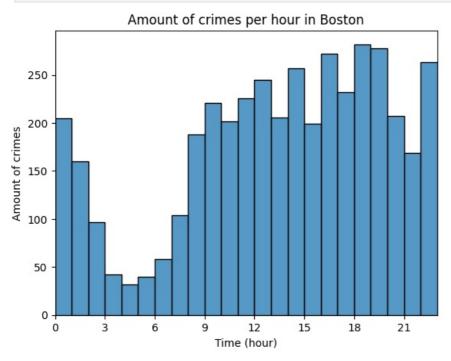
1. What are the times and days when that are most affected by crime

We need to find the relation between time, day and the amount of crimes.

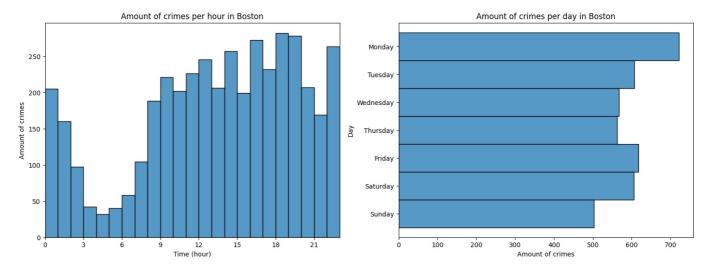
```
In [29]: sns.histplot(data=crime_df, x="Hour", binwidth=1)

# Set ticks of 3 hours on x axis
ax = plt.gca()
ax.set_xlim(0, 23)
ax.set_xticks(range(0, 24, 3))

# Add title and axis names
plt.title("Amount of crimes per hour in Boston")
plt.xlabel("Time (hour)")
plt.ylabel("Amount of crimes")
plt.show()
```



Using an histogram seems pertinent here as we just need to count values groupped by a numeric value which is our time. We should try the same with the days.



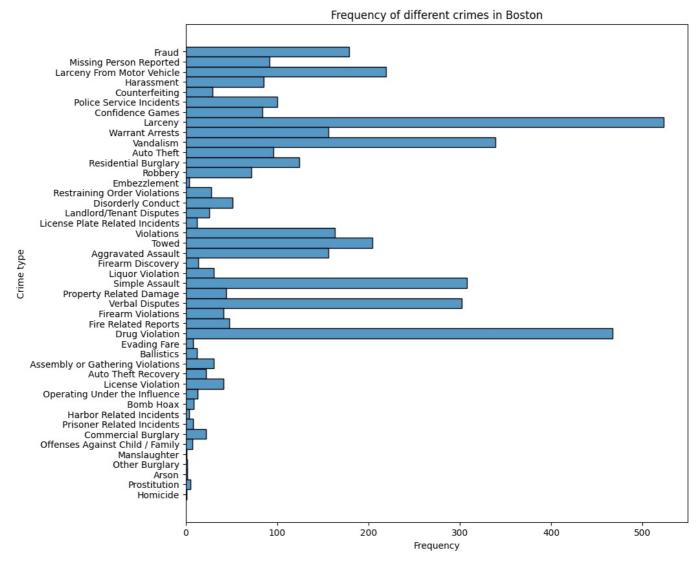
Crimes tend to happen more during the afternoon, between 4pm and 8pm. We can also observe that crimes happen more on Mondays.

### 2. What are the most frequent crimes in Boston?

Histograms are also quite useful to measure the frequency of a value across a DataFrame, let's try with one.

```
In [31]: plt.figure(figsize=(10, 10))
    sns.histplot(data=crime_df, y="Object", stat="frequency", binwidth=1)

# Set title and axis names
    plt.title("Frequency of different crimes in Boston")
    plt.ylabel("Crime type")
    plt.show()
```



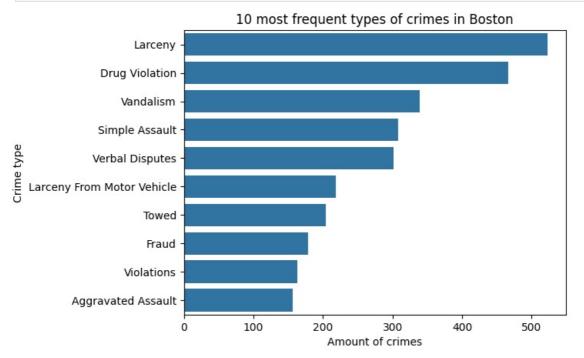
There are too much crime types for us to make a meaningful analysis, let's take the 10 most frequent crime types

instead.

```
In [32]: # Create a new DataFrame with the top 10 crime types
    top_crime_types = crime_df.groupby("Object").size().nlargest(10).index
    top_crimes_df = crime_df.loc[df["Object"].isin(top_crime_types)]

sns.countplot(data=top_crimes_df, y="Object", order=top_crimes_df["Object"].value_counts().index)

# Set title and axis names
plt.title("10 most frequent types of crimes in Boston")
plt.xlabel("Amount of crimes")
plt.ylabel("Crime type")
plt.show()
```



Obviously, the most frequent crimes in Boston are larceny drug diolation and vandalism.

# ☐ 3. Visualize using a map the amount of crimes depending their locations.

For this part, we will use folium and its heatmap to visualize crimes depending their locations.

#### 3.1 Dataset reduction

To make our map readable as we have more than 4000 elements in our DataFrame, we will use the KMeans algorithm to clusterize our locations and display them on our map. The elbow method can help us finding the good amount of clusters.

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Number of clusters

This method tells us to use around 5 clusters to have the best performance and results. For our behavior, we will use 50 clusters to have a more readable map.

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```
In [36]: from collections import Counter
         locations = crime_df[["Latitude", "Longitude"]]
         # Instanciate KMeans algorithme to reduce the amount of spots on our heatmap
         kmeans = KMeans(n_clusters=50, init="k-means++", max_iter=300, random_state=0)
         kmeans.fit(locations)
         label_counts = Counter(kmeans.labels_)
         weights = [[*kmeans.cluster_centers_[i], label_counts[kmeans.labels_[i]]] for i in range(len(kmeans.cluster_centers_in))
              Boston
                                   to center the map
       Back Bay
                                   f["Latitude"].mean(), crime df["Longitude"].mean())
                                   n=mean_location, zoom_start=12)
 y-Kenmore
                                   nap)
                  South Boston
 Roxbury
                                    to load map: File -> Trust Notebook
        Dorchester
```

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