CMSC320_FinalProject_Spring2025

April 2, 2025

1 FINAL PROJECT CHECKPOINT 2

1.1 DUE: *April 01, 2025 @ 11:59 PM*

1.2 24-HR LATE DUE DATE WITH A 15% PENALTY: *April 02, 2025 @ 11:59 PM*

1.2.1 (5 points) Data preprocessing:

(a) import
(b) parse (e.g., convert strings to ints)
(c) organize (e.g., set up a database or a pandas DataFrame)

[4]:
```
import pandas as pd
import matplotlib.pyplot as plt
import scipy.stats as stats

df = pd.read_csv('NYPD_Shooting_Incident_Data__Historic_.csv')
df.head()

# Convert date columns to datetime format
df['OCCUR_DATE'] = pd.to_datetime(df['OCCUR_DATE'], errors='coerce')

df
```

[4]:
```
       INCIDENT_KEY OCCUR_DATE OCCUR_TIME       BORO LOC_OF_OCCUR_DESC  \
0         231974218 2021-08-09   01:06:00      BRONX               NaN
1         177934247 2018-04-07   19:48:00   BROOKLYN               NaN
2         255028563 2022-12-02   22:57:00      BRONX           OUTSIDE
3          25384540 2006-11-19   01:50:00   BROOKLYN               NaN
4          72616285 2010-05-09   01:58:00      BRONX               NaN
…               …          …          …          …                 …
28557      82565818 2012-01-10   16:52:00  MANHATTAN               NaN
28558      52550581 2008-10-27   19:00:00   BROOKLYN               NaN
28559      23354135 2006-07-10   19:47:00   BROOKLYN               NaN
28560      59753078 2009-03-20   20:02:00   BROOKLYN               NaN
28561     208393713 2020-01-23   01:20:00  MANHATTAN               NaN

       PRECINCT  JURISDICTION_CODE LOC_CLASSFCTN_DESC  \
```

```
0            40                0.0                NaN
1            79                0.0                NaN
2            47                0.0             STREET
3            66                0.0                NaN
4            46                0.0                NaN
…           …                 …                  …
28557        23                2.0                NaN
28558        83                0.0                NaN
28559        60                0.0                NaN
28560        72                0.0                NaN
28561        18                0.0                NaN

                  LOCATION_DESC  STATISTICAL_MURDER_FLAG  … PERP_SEX  \
0                           NaN                    False  …       NaN
1                           NaN                     True  …         M
2                GROCERY/BODEGA                    False  …    (null)
3                     PVT HOUSE                     True  …         U
4       MULTI DWELL - APT BUILD                     True  …         M
…                           …                     …  …       …
28557  MULTI DWELL - PUBLIC HOUS                    False  …         M
28558    MULTI DWELL - APT BUILD                    False  …         M
28559                       NaN                    False  …         M
28560    MULTI DWELL - APT BUILD                    False  …         M
28561                       NaN                     True  …         M

           PERP_RACE VIC_AGE_GROUP VIC_SEX        VIC_RACE    X_COORD_CD  \
0                NaN         18-24       M           BLACK  1.006343e+06
1      WHITE HISPANIC         25-44       M           BLACK  1.000083e+06
2              (null)         25-44       M           BLACK  1.020691e+06
3             UNKNOWN         18-24       M           BLACK  9.851073e+05
4               BLACK           <18       F           BLACK  1.009854e+06
…                   …           …     …             …           …
28557  BLACK HISPANIC         25-44       M  WHITE HISPANIC  1.000102e+06
28558  WHITE HISPANIC         25-44       M  WHITE HISPANIC  1.004686e+06
28559           BLACK           <18       M           BLACK  9.841473e+05
28560  WHITE HISPANIC         18-24       M  WHITE HISPANIC  9.809204e+05
28561  WHITE HISPANIC         25-44       M           BLACK  9.861310e+05

         Y_COORD_CD   Latitude  Longitude  \
0      234270.000000  40.809673 -73.920193
1      189064.671875  40.685610 -73.942913
2      257125.000000  40.872349 -73.868233
3      173349.796875  40.642490 -73.996912
4      247502.562500  40.845984 -73.907461
…                …        …        …
28557  229680.187500  40.797089 -73.942750
28558  193261.375000  40.697119 -73.926302
```

```
28559  150277.703125  40.579162 -74.000371
28560  174343.578125  40.645217 -74.012000
28561  218089.828125  40.765291 -73.993211

                                              Lon_Lat
0       POINT (-73.92019278899994 40.80967347200004)
1      POINT (-73.94291302299996 40.685609672000055)
2                        POINT (-73.868233 40.872349)
3      POINT (-73.99691224999998 40.642489932000046)
4       POINT (-73.90746098599993 40.84598358900007)
…                                                 …
28557   POINT (-73.94275038599994 40.79708909900006)
28558  POINT (-73.92630225199997 40.697119222000026)
28559   POINT (-74.00037110599999 40.57916181000007)
28560  POINT (-74.01199971799997 40.645217064000065)
28561   POINT (-73.99321106099995 40.76529064400006)

[28562 rows x 21 columns]
```

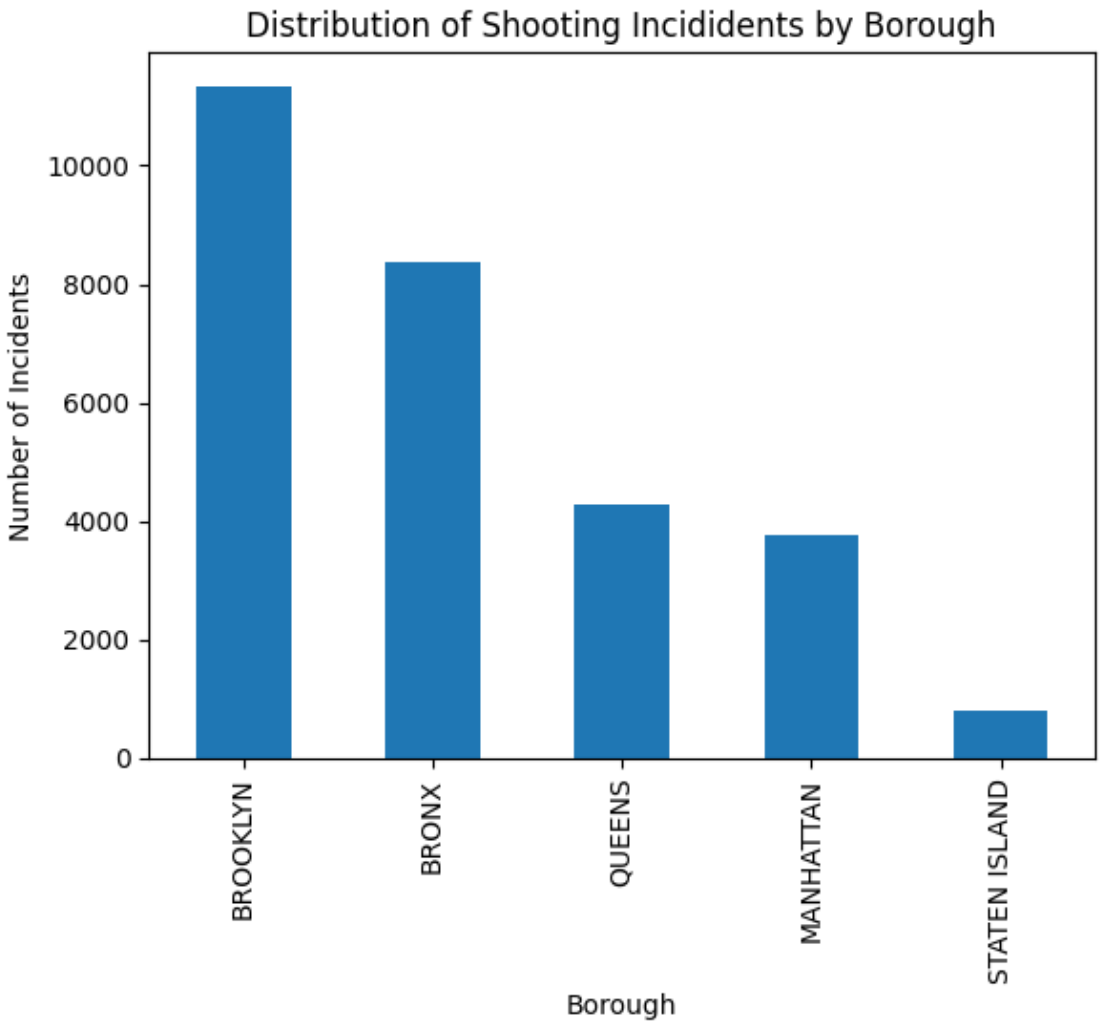
1.2.2 (20 points) Basic data exploration and summary statistics

- You must present three conclusions using at least three different statistical methods including hypothesis testing.
  - For example: What are the main characteristics of your dataset? How many features and entries are there? Is a feature over-represented? Are features correlated? Are there outliers? Identify the attributes that will affect your choice of primary analysis technique. Etcetera.
- For each method, you must have at least one gorgeous plot.

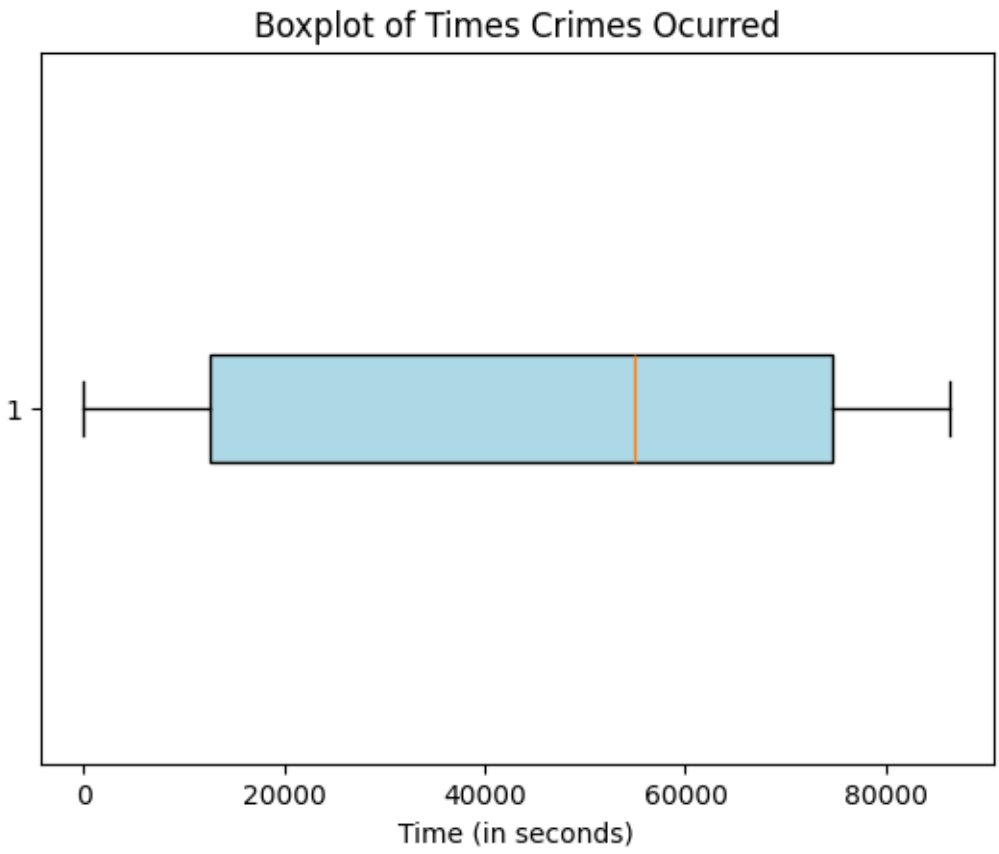
[5]:
```
# conclusion 1: Shooting incidents are not evenly distributed across boroughs
# statistical method: chi-squared test with a p-value of 0.05
# H0: there is no association between the borough and the occurence of shooting␣
 ↪incidents
# H1: There is an association, the distribution of shooting incidents is not␣
 ↪the same across all boroughs

observed = pd.crosstab(df['BORO'], df['INCIDENT_KEY']).values
chi2, p, dof, expected = stats.chi2_contingency(observed)

print(f"Chi-squared statistic: {chi2}")
print(f"p-value: {p}")

df['BORO'].value_counts().plot(kind='bar', title='Distribution of Shooting␣
 ↪Incidiidents by Borough')
plt.xlabel('Borough')
plt.ylabel('Number of Incidents')
plt.show()
```

```
# conclusion 2: The distribution of times the crimes ocurred is skewed slightly␣
 ↪to the left but doesn't have
# any outliers since the times tend to be either early in the morning or late␣
 ↪at night.
# statistical method: summary statistics

df['OCCUR_TIME'] = pd.to_datetime(df['OCCUR_TIME'], format='%H:%M:%S',␣
 ↪errors='coerce')
summary = df['OCCUR_TIME'].describe()
print("\n\nSummary statistics for the 'OCCUR_TIME' column (disregard the date):␣
 ↪\n", summary)

df['timeDelta'] = df['OCCUR_TIME'] - df['OCCUR_TIME'].min()

plt.boxplot(df['timeDelta'].dt.total_seconds(), vert=False, patch_artist=True,␣
 ↪boxprops=dict(facecolor='lightblue'))
plt.title('Boxplot of Times Crimes Ocurred')
plt.xlabel('Time (in seconds)')
plt.show()
```

```
Chi-squared statistic: 114248.0
p-value: 0.0
```

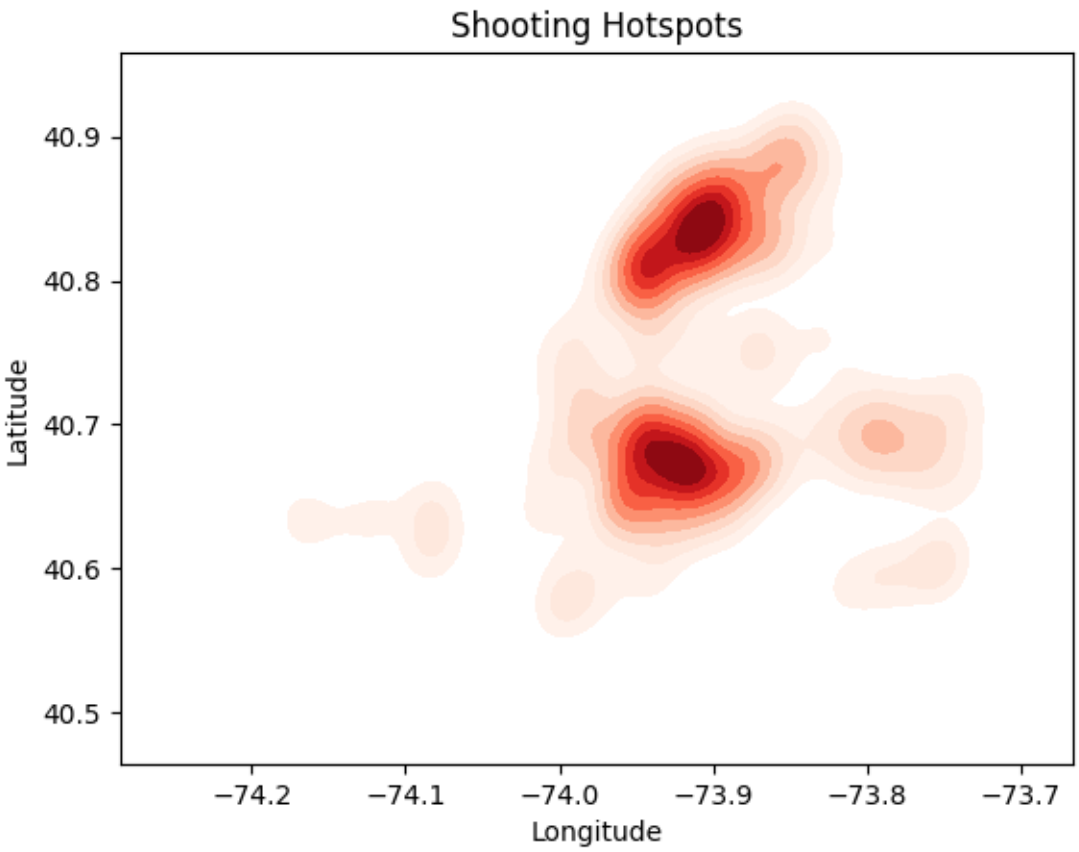


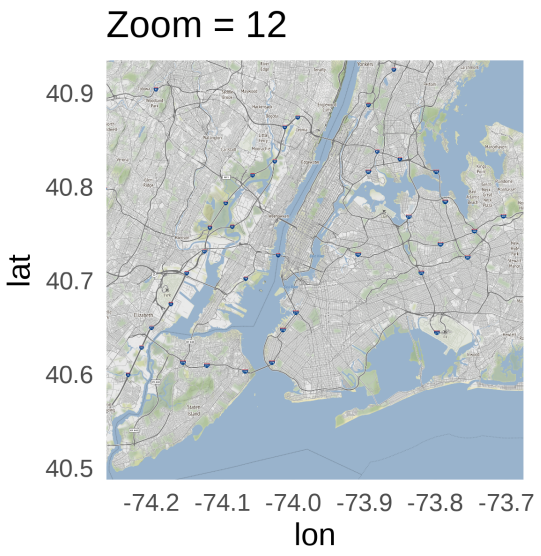

```
Summary statistics for the 'OCCUR_TIME' column (disregard the date):
 count                           28562
mean     1900-01-01 12:44:16.713115392
min                1900-01-01 00:00:00
25%                1900-01-01 03:30:00
50%                1900-01-01 15:15:00
75%                1900-01-01 20:45:00
max                1900-01-01 23:59:00
Name: OCCUR_TIME, dtype: object
```

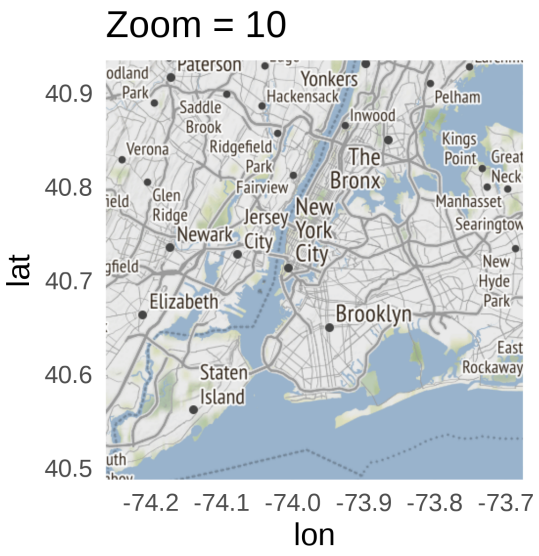


Method 3: Summarizing by most likely locations for shootings based on longitude and latitude, using a kernel density estimation from the seaborn library

[6]:
```
import seaborn as sns
import matplotlib.pyplot as plt

sns.kdeplot(x=df["Longitude"], y=df["Latitude"], cmap="Reds", fill=True)
plt.title("Shooting Hotspots")
plt.show()
```


Shooting Hotspots
Latitude
Longitude
40.9
40.8
40.7
40.6
40.5
−74.2
−74.1
−74.0
−73.9
−73.8
−73.7


Zoom = 12
lat
lon
40.9
40.8
40.7
40.6
40.5
-74.2
-74.1
-74.0
-73.9
-73.8
-73.7


Zoom = 10
lat
lon
40.9
40.8
40.7
40.6
40.5
-74.2
-74.1
-74.0
-73.9
-73.8
-73.7
Paterson
Yonkers
Hackensack
Pelham
Saddle Brook
Inwood
Ridgefield Park
Verona
The Bronx
Kings Point
Fairview
Glen Ridge
Jersey City
New York City
Manhasset
Newark
Elizabeth
Brooklyn
New Hyde Park
Staten Island
East Rockaway

src: https://info5940.infosci.cornell.edu/slides/visualize-spatial-i/index_files/figure-html/bb-nyc-stamen-zoom-1.png

Conclusions: Based on this hotspot map, most of the shootings seem centered around Brooklyn, The Bronx, and upper Manhattan. This provides a very specific visualisation of exactly where shootings tended to occur. The image below the map helps visualize exactly where the hotspot map corresponds to. It may be useful to overlay the hotspot map onto the map of NYC in the future.