Rhode Island Police Activity Analysis part 1

In [2]:

```
# Let's start with simple commands such as:


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

# Now, let's take a closer look on our dataset:

ri = pd.read_csv('Desktop/rhode-island-2019-02.csv', low_memory=False)
ri.head()
```

Out[2]:

	raw_row_number	date	time	zone	subject_race	subject_sex	department_id	type	arrest_made	citation_issued	...	contraband_weapons
0	1	2005-11-22	11:15:00	X3	white	male	200	vehicular	False	True	...	NaN
1	2	2005-10-01	12:20:00	X3	white	male	200	vehicular	False	True	...	NaN
2	3	2005-10-01	12:30:00	X3	white	female	200	vehicular	False	True	...	NaN
3	4	2005-10-01	12:50:00	X3	white	male	200	vehicular	False	True	...	NaN
4	5	2005-10-01	13:10:00	X3	white	female	200	vehicular	False	True	...	NaN

5 rows × 24 columns

NaN values

In [12]:

```
# let's check if there are null values in our dataset
ri.isnull().head()
```

Out[12]:

	raw_row_number	date	time	zone	subject_race	subject_sex	department_id	type	arrest_made	citation_issued	...	contraband_weapons	contr
0	False	False	False	False	False	False	False	False	False	False	...	True	
1	False	False	False	False	False	False	False	False	False	False	...	True	
2	False	False	False	False	False	False	False	False	False	False	...	True	
3	False	False	False	False	False	False	False	False	False	False	...	True	
4	False	False	False	False	False	False	False	False	False	False	...	True	

5 rows × 24 columns

Dropping NaN values

In [13]:

```
# Now we take a look at what columns to drop
# (or in case there are no columns to drop, it will help us to better understand our dataset, therefore this step is
# helpful)
ri.isnull().sum()
```

Out[13]:

```
raw_row_number           0
date                    10
time                    10
zone                    10
subject_race         29073
subject_sex          29097
department_id           10
type                     0
arrest_made          29073
citation_issued      29073
warning_issued       29073
outcome              35841
contraband_found    491919
contraband_drugs    493693
contraband_weapons  497886
contraband_alcohol  508464
contraband_other         0
frisk_performed         10
search_conducted        10
search_basis        491919
reason_for_search   491919
reason_for_stop      29073
vehicle_make        191564
vehicle_model       279593
dtype: int64
```

In [14]:

```
# in order to know which columns to drop, we need to print the shape of our dataset:

ri.shape
```

Out[14]:

```
(509681, 24)
```

In [ ]:

```
# in this case there is no column we can drop, because none of the columns is completely empty, but for the
# purpose of this analysis we will drop three columns: 'contraband_alcohol', 'contraband_weapons', 'search_basis'
```

Dropping empty columns and rows

In [15]:

```
ri.drop('contraband_alcohol', axis='columns', inplace=True)
```

In [16]:

```
ri.drop('contraband_weapons', axis='columns', inplace=True)
```

In [17]:

```
ri.drop('search_basis', axis='columns', inplace=True)
```

In [86]:

```
# Let's make sure the columns were actually dropped by printing head of the dataset:

ri.head()
```

Out[86]:

	raw_row_number	date	time	zone	subject_race	subject_sex	department_id	type	arrest_made	citation_issued	...	contraband_weapons
0	1	2005-11-22	11:15:00	X3	white	male	200	vehicular	False	True	...	NaN
1	2	2005-10-01	12:20:00	X3	white	male	200	vehicular	False	True	...	NaN
2	3	2005-10-01	12:30:00	X3	white	female	200	vehicular	False	True	...	NaN
		2005-										

	raw_row_number	date	time	zone	subject_race	subject_sex	department_id	type	arrest_made	citation_issued	...	contraband_weapons
3	4	2005-10-01	12:50:00	X3	white	male	200	vehicular	False	True	...	NaN
4	5	2005-10-01	13:10:00	X3	white	female	200	vehicular	False	True	...	NaN

5 rows × 24 columns

In [19]:

```
# now we drop NaN rows from columns 'reason_for_search' and 'vehicle_model' to make the analysis easier for us

ri.dropna(subset=['reason_for_search', 'vehicle_model'], inplace=True)
```

In [20]:

```
ri.isnull().head()
```

Out[20]:

	raw_row_number	date	time	zone	subject_race	subject_sex	department_id	type	arrest_made	citation_issued	...	outcome	contraband_fo
297	False	False	False	False	False	False	False	False	False	False	...	False	F
634	False	False	False	False	False	False	False	False	False	False	...	False	F
1218	False	False	False	False	False	False	False	False	False	False	...	False	F
1239	False	False	False	False	False	False	False	False	False	False	...	False	F
1299	False	False	False	False	False	False	False	False	False	False	...	False	F

5 rows × 21 columns

Fixing dtypes and correcting formats

In [21]:

```
# for smoother manipulation with our data, we need to change current data types of some columns in our dataset

ri.dtypes    # in this case, we start with printing the data types first
```

Out[21]:

```
raw_row_number       int64
date                object
time                object
zone                object
subject_race        object
subject_sex         object
department_id       object
type                object
arrest_made         object
citation_issued     object
warning_issued      object
outcome             object
contraband_found    object
contraband_drugs    object
contraband_other      bool
frisk_performed     object
search_conducted    object
reason_for_search   object
reason_for_stop     object
vehicle_make        object
vehicle_model       object
dtype: object
```

In [22]:

```
# To get answers and draw conclusions from our data we choose to change the data types of 'arrest_made' and
#'citation_issued' from 'object' to 'bool'(boolean)

ri['arrest_made'] = ri.arrest_made.astype('bool')
```

In [23]:

```
ri['citation_issued'] = ri.citation_issued.astype('bool')
```

```
ri['citation_issued'] = ri.citation_issued.astype('bool')
```

In [24]:

```
#Combine date and time column in "combined" with space in between


combined = ri.date.str.cat(ri.time, sep=' ')
```

In [25]:

```
combined.head()
```

Out[25]:

```
297     2005-12-06 16:29:00
634     2005-12-07 19:40:00
1218    2005-12-13 08:41:00
1239    2005-12-13 10:41:00
1299    2005-12-08 17:41:00
Name: date, dtype: object
```

In [26]:

```
#create a new column called date_and_time from combined, use pandas method to_datetime

ri['date_and_time'] = pd.to_datetime(combined)
```

In [27]:

```
ri.head()
```

Out[27]:

	raw_row_number	date	time	zone	subject_race	subject_sex	department_id	type	arrest_made	citation_issued	...	contraband_found
297	298	2005-12-06	16:29:00	K2	black	male	900	vehicular	False	True	...	False
634	635	2005-12-07	19:40:00	K3	white	male	300	vehicular	True	False	...	False
1218	1219	2005-12-13	08:41:00	X4	black	female	900	vehicular	True	False	...	False
1239	1240	2005-12-13	10:41:00	X4	black	male	900	vehicular	False	True	...	False
1299	1300	2005-12-08	17:41:00	K2	white	male	900	vehicular	False	True	...	False

5 rows × 22 columns

In [28]:

```
# let's make sure the column we've created has also the desired data type

ri.dtypes
```

Out[28]:

```
raw_row_number        int64
date                 object
time                 object
zone                 object
subject_race         object
subject_sex          object
department_id        object
type                 object
arrest_made            bool
citation_issued        bool
warning_issued       object
outcome              object
contraband_found     object
contraband_drugs     object
contraband_other       bool
frisk_performed      object
search_conducted     object
```

```
reason_for_search          object
reason_for_stop            object
vehicle_make               object
vehicle_model              object
date_and_time      datetime64[ns]
dtype: object
```

Setting index

In [29]:

```
#let's set the column date_and_time as an index column

ri.set_index('date_and_time', inplace=True)
```

In [30]:

```
ri.head()
```

Out[30]:

date_and_time	raw_row_number	date	time	zone	subject_race	subject_sex	department_id	type	arrest_made	citation_issued	...	outcome
2005-12-06 16:29:00	298	2005-12-06	16:29:00	K2	black	male	900	vehicular	False	True	...	citation
2005-12-07 19:40:00	635	2005-12-07	19:40:00	K3	white	male	300	vehicular	True	False	...	arrest
2005-12-13 08:41:00	1219	2005-12-13	08:41:00	X4	black	female	900	vehicular	True	False	...	arrest
2005-12-13 10:41:00	1240	2005-12-13	10:41:00	X4	black	male	900	vehicular	False	True	...	citation
2005-12-08 17:41:00	1300	2005-12-08	17:41:00	K2	white	male	900	vehicular	False	True	...	citation

5 rows × 21 columns

1. Most common outcome of a police stop

In [18]:

```
outcomes=ri.outcome.value_counts()
print(outcomes)

# citation or also known as a ticket, is the most common outcome of a police stop
```

```
citation    428388
warning      28849
arrest       16603
Name: outcome, dtype: int64
```

2. Most common traffic violation

In [46]:

```
ri.reason_for_stop.value_counts()        # from 'Call for Service' named as 'other'
```

Out[46]:

```
Speeding                          2707
Other Traffic Violation           2596
Equipment/Inspection Violation    2157
Registration Violation             854
Seatbelt Violation                 398
Call for Service                   273
Suspicious Person                   51
Special Detail/Directed Patrol      48
APB                                 37
Motorist Assist/Courtesy            34
```

```
Motorist Assist/Courtesy          34
Violation of City/Town Ordinance      20
Warrant                           16
Name: reason_for_stop, dtype: int64
```

In [47]:

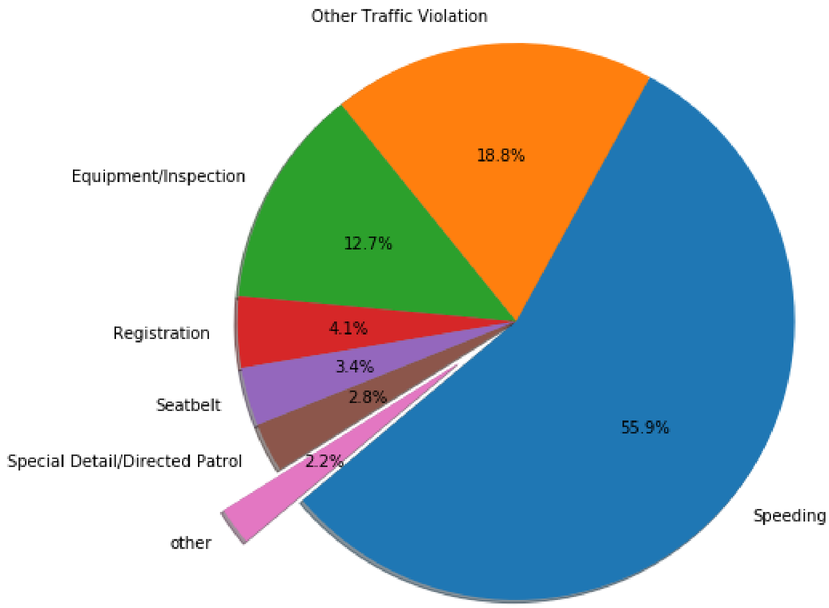
```
# let's create a visual pie chart to see what are the most common traffic violations

labels = ['Speeding', 'Other Traffic Violation', 'Equipment/Inspection', 'Registration',
'Seatbelt', 'Special Detail/Directed Patrol', 'other']
sizes = [268744,90234,61252,19830,16327,13642,10576]
plt.axis('equal')
plt.pie(sizes, labels=labels, radius=2, autopct='%1.1f%%', shadow=True, startangle=220, explode=[0,0,0,0,0,0,0.5])
;

# 'other' contains = Call for Service, Violation of City/Town Ordinance, Motorist Assist/Courtesy, APB,
#  Suspicious Person and Warrant
```

Out[47]:

''



3.Comparing violations by gender

In [61]:

```
# let's take a closer look at the difference between violations committed by men and violations committed by women,
# is there a difference?


female = ri[ri.subject_sex == 'female']
male = ri[ri.subject_sex == 'male']

resultfemale= female.reason_for_stop.value_counts(normalize=True)
print(resultfemale)

resultmale=male.reason_for_stop.value_counts(normalize=True)
print(resultmale)
```

```
Speeding                          0.657308
Other Traffic Violation           0.136581
Equipment/Inspection Violation    0.107055
Registration Violation            0.043077
Seatbelt Violation                0.027071
Call for Service                  0.018057
Special Detail/Directed Patrol    0.005071
Motorist Assist/Courtesy          0.002532
Violation of City/Town Ordinance  0.001647
APB                               0.000831
Suspicious Person                 0.000564
Warrant                           0.000206
Name: reason_for_stop, dtype: float64
Speeding                          0.522364
```

```
Other Traffic Violation         0.206948
Equipment/Inspection Violation    0.135102
Registration Violation          0.040581
Special Detail/Directed Patrol    0.037136
Seatbelt Violation              0.036555
Call for Service                0.014987
Violation of City/Town Ordinance    0.002347
Motorist Assist/Courtesy          0.001880
APB                             0.001076
Suspicious Person               0.000767
Warrant                         0.000258
Name: reason_for_stop, dtype: float64
```

In [ ]:

```
# as we can see women are more likely to speed than men, on the other hand they are less likely to commit the
# other two most common violations 'Other Traffic Violation' and 'Equipment/Inspection Violation'
```

4. Does gender affect whether your car will be searched?

In [83]:

```
female=ri[ri.subject_sex == 'female'].search_conducted.mean()
print(female)
male=ri[ri.subject_sex == 'male'].search_conducted.mean()
print(male)

                                        # Women seem to be less likely to have their car searched, but to
                                        # make sure our conclusions are correct, we have to find out the total
                                        # number of searches

femaletotal=ri[ri.subject_sex == 'female'].search_conducted.sum()
maletotal=ri[ri.subject_sex == 'male'].search_conducted.sum()

print(femaletotal)
print(maletotal)
```

```
0.018751239152648355
0.04379217389811301
2459
15303
```

In [ ]:

```
# ^ We see clearly, that drawing conclusion based on one result can significantly distort overall understanding of out
# data, specifically in this case there were around 6.2 times more men having their car searched than women and
# therefore the mean of women having their car searched was lower because the total number of women having
# their car searched was 6.2 times less.
```

In [16]:

```
# if we take a closer look on the connection between reason for stop, the search itself and gender we see that the
# most common reason why both genders had their car searched was "Speeding" and "Other Traffic Violation" and
# eventually "Equipment/Inspection Violation"

#given the proportions there's no significant difference except, women were more likely to be stopped for
# "Other Traffic Violation" than men

ri.groupby(['subject_sex', 'reason_for_stop']).search_conducted.sum()
```

Out[16]:

```
subject_sex  reason_for_stop
female       APB                                  18
             Call for Service                    100
             Equipment/Inspection Violation      565
             Motorist Assist/Courtesy             11
             Other Traffic Violation             681
             Registration Violation              309
             Seatbelt Violation                   63
             Special Detail/Directed Patrol       12
             Speeding                            667
             Suspicious Person                    16
             Violation of City/Town Ordinance     13
             Warrant                               4
male         APB                                  96
```

```
          Call for Service                 484
          Equipment/Inspection Violation    3348
          Motorist Assist/Courtesy            59
          Other Traffic Violation           4278
          Registration Violation            1469
          Seatbelt Violation                 405
          Special Detail/Directed Patrol     133
          Speeding                          4861
          Suspicious Person                   82
          Violation of City/Town Ordinance    60
          Warrant                             28
Name: search_conducted, dtype: int64
```

5. Arrest rate

In [79]:

```python
ri.arrest_made.value_counts(normalize=True)


#We can see the arrest rate is around 3,4 %
```

Out[79]:

```
False    0.965454
True     0.034546
Name: arrest_made, dtype: float64
```

6. Arrest rate by district

In [87]:

```python
ri.zone.unique()

# Let's find out the names of the districts with the .unique() method, we need to know the names of the zones first
# to move on with our analysis
```

Out[87]:

```
array(['X3', 'X4', 'K3', 'K2', 'K1', 'X1', nan], dtype=object)
```

In [11]:

```python
# in order to find out which district has the highest arrest rate and which one the lowest we will filter the
# dataset by each zone

x3=ri[ri.zone == 'X3'].arrest_made.mean()
print(x3)

x4=ri[ri.zone == 'X4'].arrest_made.mean()
print(x4)

k3=ri[ri.zone == 'K3'].arrest_made.mean()
print(k3)

k2=ri[ri.zone == 'K2'].arrest_made.mean()
print(k2)

k1=ri[ri.zone == 'K1'].arrest_made.mean()
print(k1)

x1=ri[ri.zone == 'X1'].arrest_made.mean()
print(x1)


# as we can see, the highest arrest rate is in the zone X4, on the contrary the lowest arrest rate is in zone K1



all=ri.groupby('zone').arrest_made.sum()    # let's take into consideration the total sum of arrests made in each
                                            # zone
print(all)
```

```
0.033353086530183255
0.047289393903225035
0.03201836969001148
```

```
0.03201836969001148
0.02812442178409161
0.024047531279137845
0.02616454930429522
zone
K1    1109
K2    2736
K3    3486
X1     346
X3    2983
X4    5943
Name: arrest_made, dtype: int64
```

In [10]:

```python
# ^ After printing the sum of arrests made we can see our conclusion was not completely correct, the average or the
# mean number of arrests is the lowest in zone K1 but the amount of arrests is the lowest in zone X1.

#
#

# To find out more information about the relation between gender and arrest we use the groupby method once again,
# this time we add a second factor 'subject_sex'

ri.groupby(['zone', 'subject_sex']).arrest_made.sum()
```

Out[10]:

```
zone  subject_sex
K1    female          213
      male            896
K2    female          549
      male           2187
K3    female          658
      male           2828
X1    female           56
      male            290
X3    female          695
      male           2288
X4    female         1172
      male           4771
Name: arrest_made, dtype: int64
```

In [ ]:

```python
# Arrests of men seem to be approximately 4-5 times higher than arrests of women in all zones.
```