In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use('seaborn')
import seaborn as sns
import scipy as sp
import gc
```

In [3]:
```
fileURL = './tmpsdhjynao.csv'
crime_data = pd.read_csv(fileURL, header=0)
```

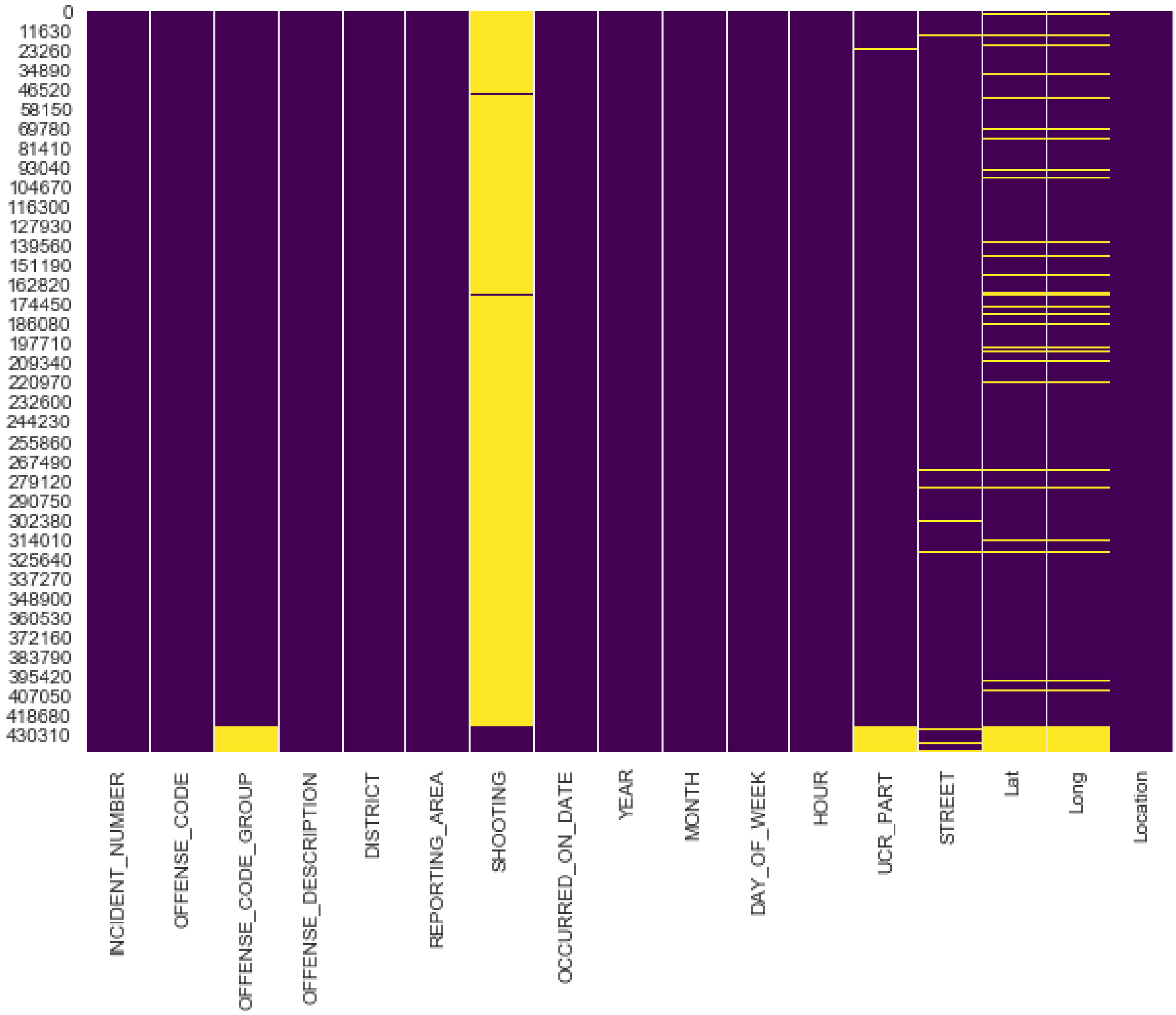
In [4]:
```
crime_data.head()
```

Out[4]:

	INCIDENT_NUMBER	OFFENSE_CODE	OFFENSE_CODE_GROUP	OFFENSE_DESCRIPTION	DIS
0	TESTTEST2	423	NaN	ASSAULT - AGGRAVATED	E
1	I92094519	3126	NaN	WARRANT ARREST - OUTSIDE OF BOSTON WARRANT	
2	I92089785	3005	NaN	SICK ASSIST	
3	I90583827	1402	NaN	VANDALISM	
4	I192082859	724	Auto Theft	AUTO THEFT	

In [5]:
```
plt.figure(figsize=(10,7))
sns.heatmap(crime_data.isnull(), cbar = False, cmap = 'viridis')
```

Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x24ae68afda0>

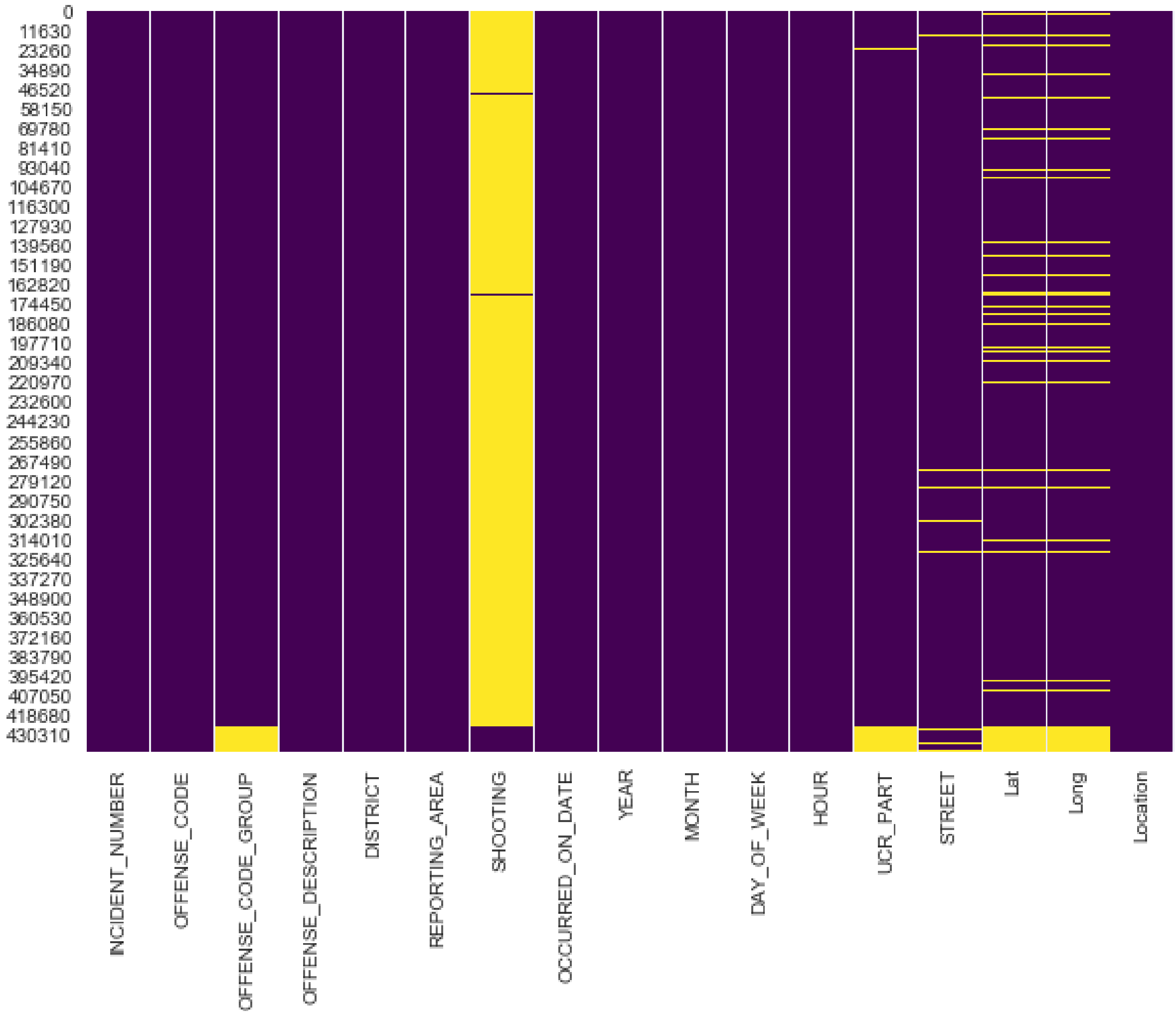


In [6]:
```
crime_data.shape
```

Out[6]: (441916, 17)

In [7]:
```
plt.figure(figsize=(10,7))
sns.heatmap(crime_data.isnull(), cbar = False, cmap = 'viridis')
```

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x24ae68f84e0>



In [8]:
```
crime_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 441916 entries, 0 to 441915
Data columns (total 17 columns):
INCIDENT_NUMBER        441916 non-null object
OFFENSE_CODE           441916 non-null int64
OFFENSE_CODE_GROUP     426840 non-null object
OFFENSE_DESCRIPTION    441916 non-null object
DISTRICT               439664 non-null object
REPORTING_AREA         441916 non-null object
SHOOTING               16823 non-null object
OCCURRED_ON_DATE       441916 non-null object
YEAR                   441916 non-null int64
MONTH                  441916 non-null int64
DAY_OF_WEEK            441916 non-null object
HOUR                   441916 non-null int64
UCR_PART               426730 non-null object
STREET                 427958 non-null object
Lat                    399636 non-null float64
Long                   399636 non-null float64
Location               441916 non-null object
dtypes: float64(2), int64(4), object(11)
memory usage: 57.3+ MB
```

In [9]:
```
# Statistical data of the number of missing values
print("boston_crimes dataset: missing values check")
crime_data= crime_data.replace('?', np.NaN)
crime_data = crime_data.replace(r'^\s*$', np.nan, regex=True)
crime_data.isnull().sum()
```

```
boston_crimes dataset: missing values check
```

Out[9]:
```
INCIDENT_NUMBER             0
OFFENSE_CODE                0
OFFENSE_CODE_GROUP      15076
OFFENSE_DESCRIPTION         0
DISTRICT                 2252
REPORTING_AREA          29141
SHOOTING               425093
OCCURRED_ON_DATE            0
YEAR                        0
MONTH                       0
DAY_OF_WEEK                 0
HOUR                        0
UCR_PART                15186
STREET                  13958
Lat                     42280
Long                    42280
Location                    0
dtype: int64
```

In [10]:
```
crime_data = crime_data.iloc[1:]
crime_data = crime_data.dropna()
```

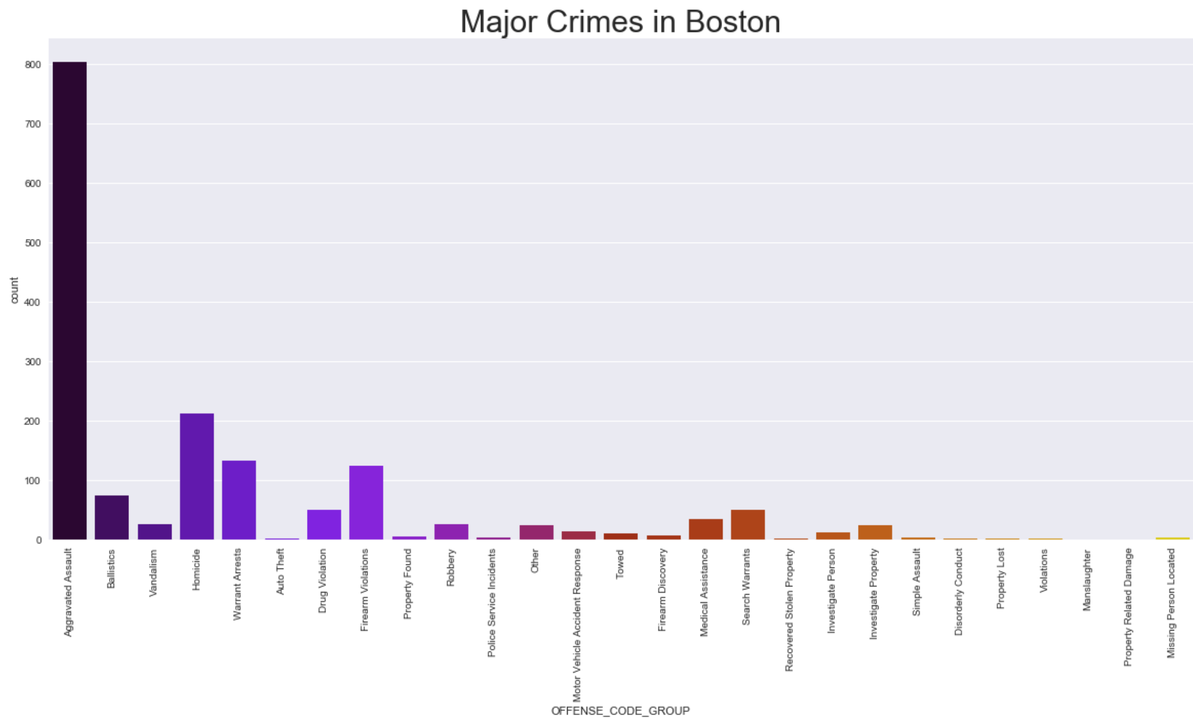
In [11]:
```
crime_data['OCCURRED_ON_DATE']= pd.to_datetime(crime_data['OCCURRED_ON_DATE'],
format='%Y-%m-%d %H:%M:%S' , errors='coerce')
```

In [12]:
```
crime_data.info()
```

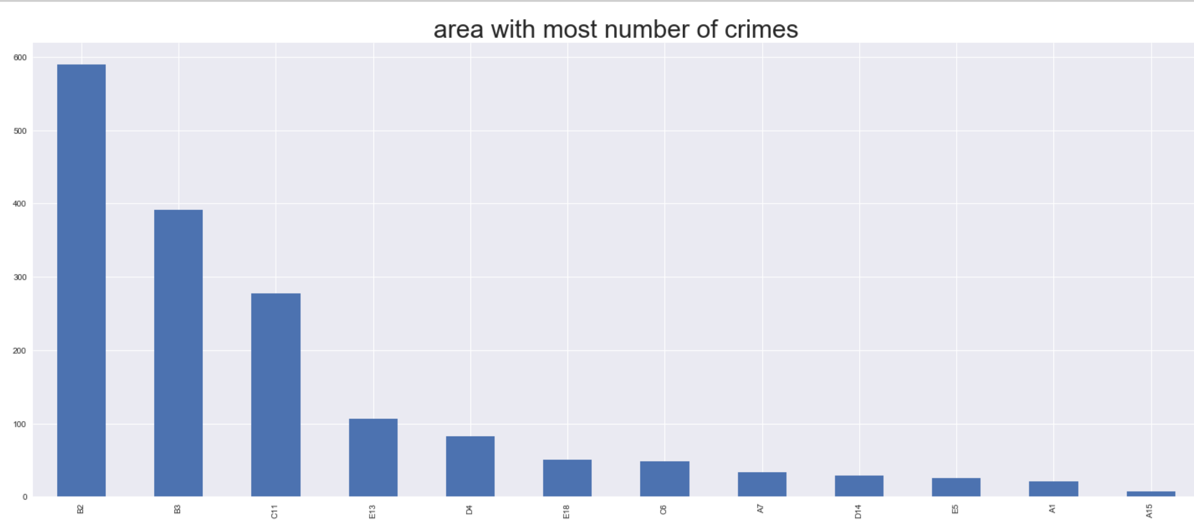
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1663 entries, 876 to 426308
Data columns (total 17 columns):
INCIDENT_NUMBER        1663 non-null object
OFFENSE_CODE           1663 non-null int64
OFFENSE_CODE_GROUP     1663 non-null object
OFFENSE_DESCRIPTION    1663 non-null object
DISTRICT               1663 non-null object
REPORTING_AREA         1663 non-null object
SHOOTING               1663 non-null object
OCCURRED_ON_DATE       1663 non-null datetime64[ns]
YEAR                   1663 non-null int64
MONTH                  1663 non-null int64
DAY_OF_WEEK            1663 non-null object
HOUR                   1663 non-null int64
UCR_PART               1663 non-null object
STREET                 1663 non-null object
Lat                    1663 non-null float64
Long                   1663 non-null float64
Location               1663 non-null object
dtypes: datetime64[ns](1), float64(2), int64(4), object(10)
memory usage: 233.9+ KB
```

Initial Data Analysis

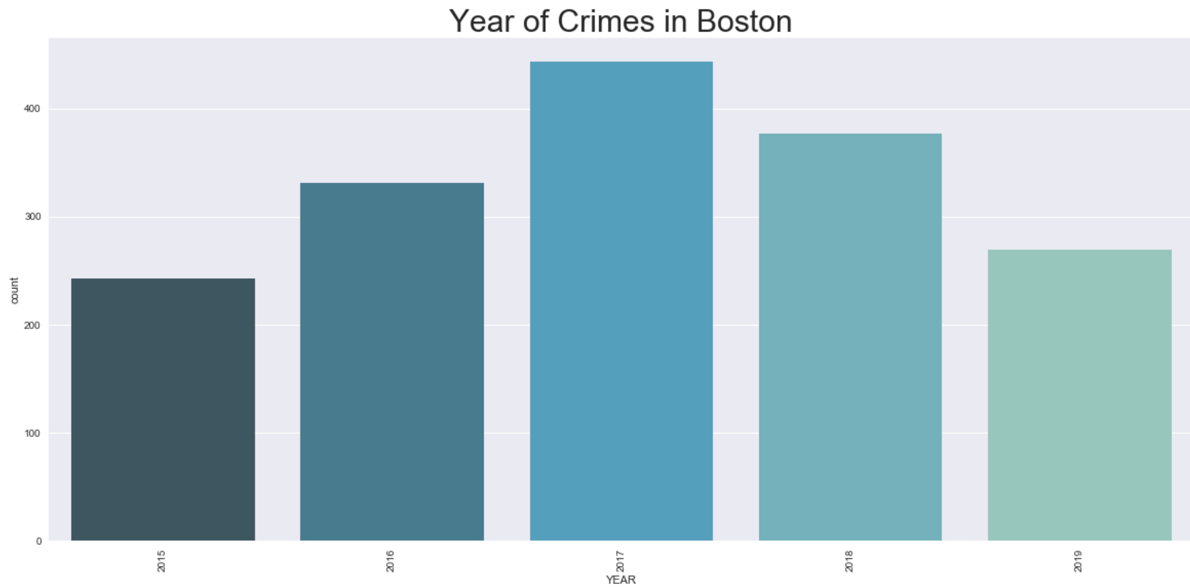
In [13]:
```
# Crimes according to crime type
plt.rcParams['figure.figsize'] = (20, 9)
sns.countplot(crime_data['OFFENSE_CODE_GROUP'], palette = 'gnuplot')
plt.title('Major Crimes in Boston', fontsize = 30)
plt.xticks(rotation = 90)
plt.show()
```



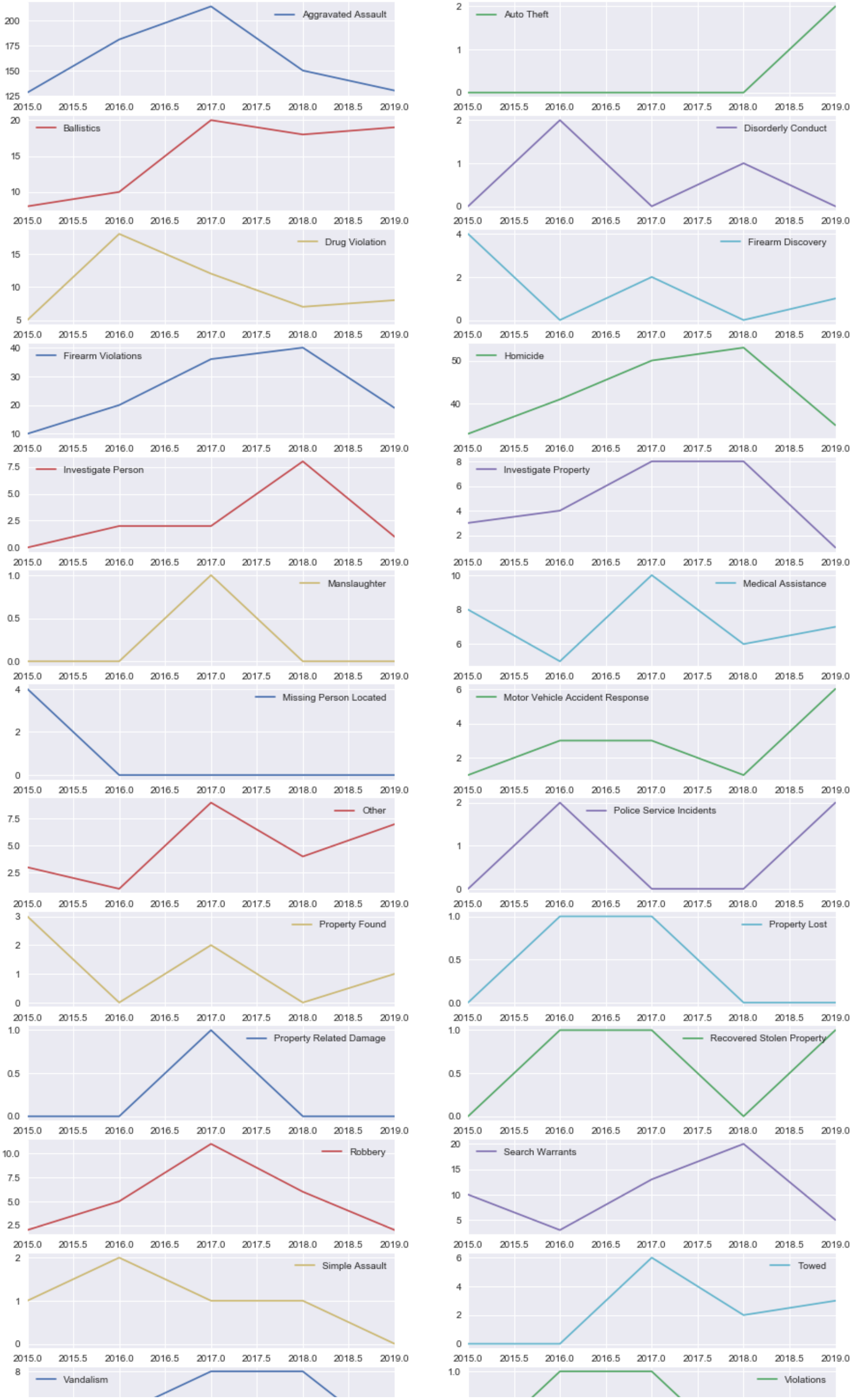
In [14]:
```
# Districts with count of respective crimes

plt.rcParams['figure.figsize'] = (20, 9)
plt.style.use('seaborn')

crime_data['DISTRICT'].value_counts().plot.bar(figsize = (25, 10))

plt.title('area with most number of crimes',fontsize = 30)

plt.xticks(rotation = 90)
plt.show()
```



In [15]:
```
plt.rcParams['figure.figsize'] = (20, 9)
sns.countplot(crime_data['YEAR'], palette = 'GnBu_d')
plt.title('Year of Crimes in Boston', fontsize = 30)
plt.xticks(rotation = 90)
plt.show()
```



In [16]:
```
# crime based on the crime type through the years
crimes_count_date = crime_data.pivot_table('INCIDENT_NUMBER', aggfunc=np.size,
columns='OFFENSE_CODE_GROUP', index=crime_data['YEAR'], fill_value=0)
plo_ct = crimes_count_date.plot(figsize=(15, 30), subplots=True, layout=(-1, 2
), sharex=False, sharey=False)
```


Aggravated Assault
Auto Theft
Ballistics
Disorderly Conduct
Drug Violation
Firearm Discovery
Firearm Violations
Homicide
Investigate Person
Investigate Property
Manslaughter
Medical Assistance
Missing Person Located
Motor Vehicle Accident Response
Other
Police Service Incidents
Property Found
Property Lost
Property Related Damage
Recovered Stolen Property
Robbery
Search Warrants
Simple Assault
Towed
Vandalism
Violations
2015.0 2015.5 2016.0 2016.5 2017.0 2017.5 2018.0 2018.5 2019.0

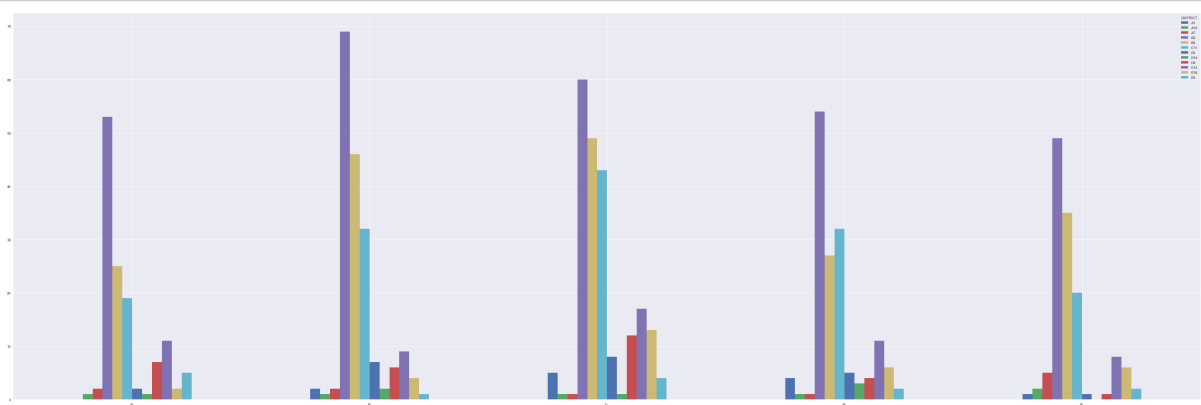
In [17]:
```python
# crime based on the crime type through the years in each district
crimes_count_date = crime_data.pivot_table('INCIDENT_NUMBER', aggfunc=np.size, columns=['OFFENSE_CODE_GROUP', 'DISTRICT'], index=crime_data['YEAR'], fill_value=0)
crimes_count_date.head()
```

Out[17]:

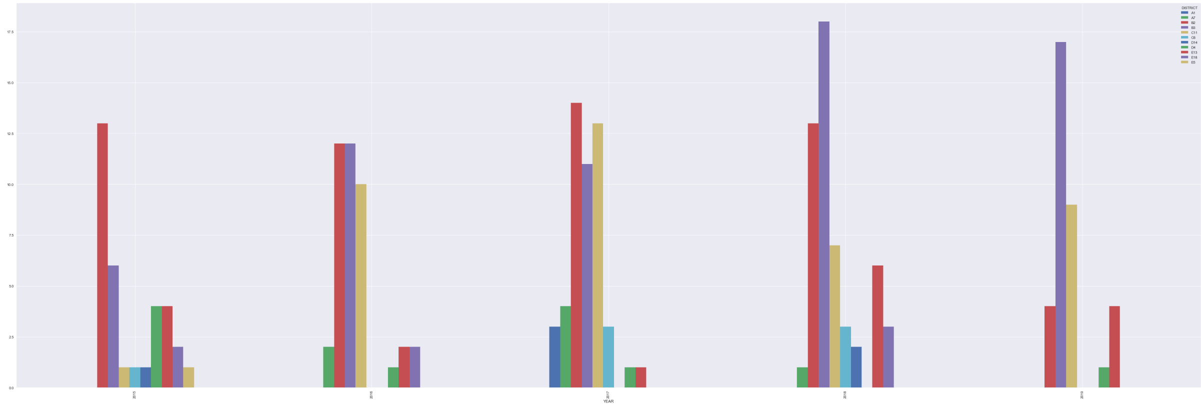
OFFENSE_CODE_GROUP	Aggravated Assault										...	Warrant Arrests			
DISTRICT	A1	A15	A7	B2	B3	C11	C6	D14	D4	E13	...	A7	B2	B3	C11
YEAR															
2015	0	1	2	53	25	19	2	1	7	11	...	0	7	3	1
2016	2	1	2	69	46	32	7	2	6	9	...	0	14	6	2
2017	5	1	1	60	49	43	8	1	12	17	...	0	10	4	4
2018	4	1	1	54	27	32	5	3	4	11	...	1	18	10	3
2019	1	2	5	49	35	20	1	0	1	8	...	2	6	4	1

5 rows × 148 columns

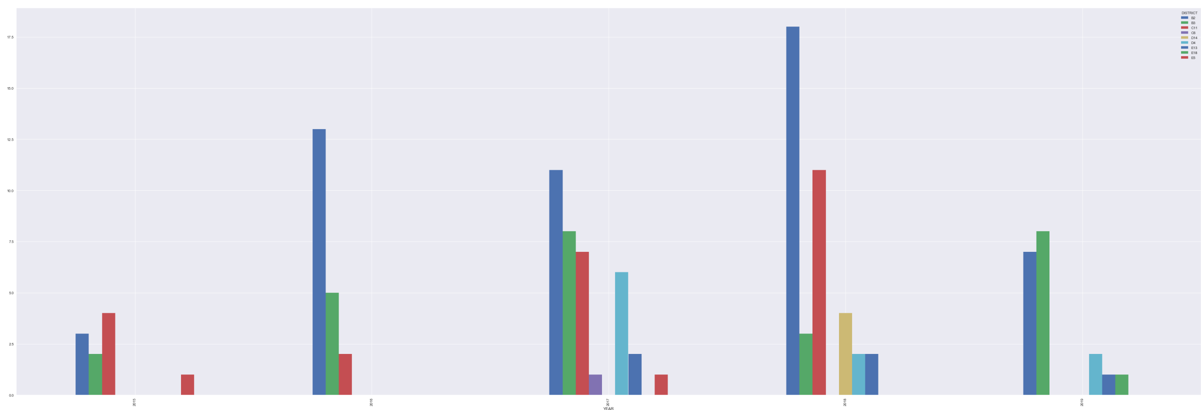
In [18]:
```python
#Plot of Aggravated Assault throughout the years in various districts
plo_assault = crimes_count_date['Aggravated Assault'].plot(figsize=(60,20),sharex=False, sharey=False , kind='bar')
```



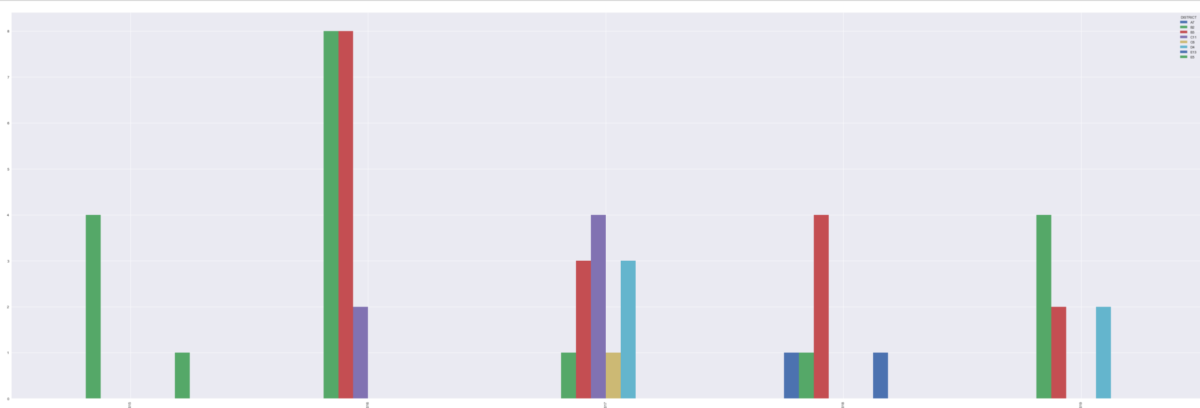
In [19]:
```
#Plot of Homicide throughout the years in various districts
plo_assault = crimes_count_date['Homicide'].plot(figsize=(60,20),sharex=False,
sharey=False , kind='bar')
```



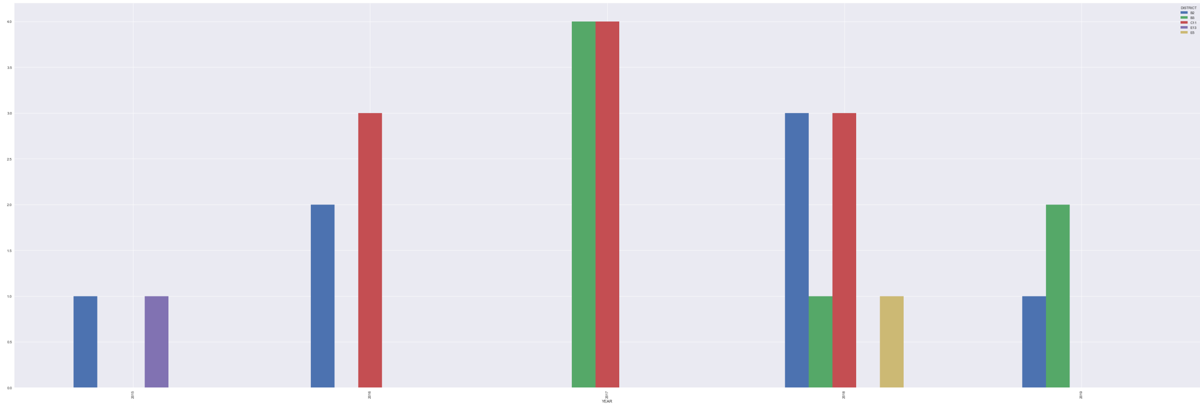
In [20]:
```
#Plot of Firearm Violations throughout the years in various districts
plo_assault = crimes_count_date['Firearm Violations'].plot(figsize=(60,20),sha
rex=False, sharey=False , kind='bar')
```



In [21]:
```
#Plot of Drug Violation throughout the years in various districts
plo_assault = crimes_count_date['Drug Violation'].plot(figsize=(60,20),sharex=
False, sharey=False , kind='bar')
```



In [22]:
```
#Plot of Vandalism throughout the years in various districts
plo_assault = crimes_count_date['Vandalism'].plot(figsize=(60,20),sharex=False
, sharey=False , kind='bar')
```



Classification - Random Forest

In [23]:
```
#Let us first see the different types of crimes in Boston. This information is
contained in 'Offense code group' feature of the dataset
crime_data['OFFENSE_CODE_GROUP'].value_counts()
```

Out[23]:
```
Aggravated Assault                  803
Homicide                            212
Warrant Arrests                     133
Firearm Violations                  125
Ballistics                           75
Search Warrants                      51
Drug Violation                       50
Medical Assistance                   36
Vandalism                            26
Robbery                              26
Other                                24
Investigate Property                 24
Motor Vehicle Accident Response      14
Investigate Person                   13
Towed                                11
Firearm Discovery                     7
Property Found                        6
Simple Assault                        5
Police Service Incidents              4
Missing Person Located                4
Disorderly Conduct                    3
Recovered Stolen Property             3
Property Lost                         2
Auto Theft                            2
Violations                            2
Property Related Damage               1
Manslaughter                          1
Name: OFFENSE_CODE_GROUP, dtype: int64
```

In [24]:
```
#There are 27 different types of crimes that are used to classify any given da
ta under
uniquePrimaryType= crime_data['OFFENSE_CODE_GROUP'].unique()
print(uniquePrimaryType)
crime_data['OFFENSE_CODE_GROUP'].nunique()
```

```
['Aggravated Assault' 'Ballistics' 'Vandalism' 'Homicide'
 'Warrant Arrests' 'Auto Theft' 'Drug Violation' 'Firearm Violations'
 'Property Found' 'Robbery' 'Police Service Incidents' 'Other'
 'Motor Vehicle Accident Response' 'Towed' 'Firearm Discovery'
 'Medical Assistance' 'Search Warrants' 'Recovered Stolen Property'
 'Investigate Person' 'Investigate Property' 'Simple Assault'
 'Disorderly Conduct' 'Property Lost' 'Violations' 'Manslaughter'
 'Property Related Damage' 'Missing Person Located']
```

Out[24]: 27

In [25]:
```
#Using a copy of the datset to manipulate the values for classification
rfboston = crime_data.copy(deep=True)
```

In [26]:
```
rfboston.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1663 entries, 876 to 426308
Data columns (total 17 columns):
INCIDENT_NUMBER         1663 non-null object
OFFENSE_CODE            1663 non-null int64
OFFENSE_CODE_GROUP      1663 non-null object
OFFENSE_DESCRIPTION     1663 non-null object
DISTRICT                1663 non-null object
REPORTING_AREA          1663 non-null object
SHOOTING                1663 non-null object
OCCURRED_ON_DATE        1663 non-null datetime64[ns]
YEAR                    1663 non-null int64
MONTH                   1663 non-null int64
DAY_OF_WEEK             1663 non-null object
HOUR                    1663 non-null int64
UCR_PART                1663 non-null object
STREET                  1663 non-null object
Lat                     1663 non-null float64
Long                    1663 non-null float64
Location                1663 non-null object
dtypes: datetime64[ns](1), float64(2), int64(4), object(10)
memory usage: 233.9+ KB
```

In [27]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
```

In [28]:
```
#Creating the dependent variable class
factor = pd.factorize(rfboston['OFFENSE_CODE_GROUP'])
rfboston.species = factor[0]
definitions = factor[1]
print(rfboston.species)
print(definitions)
```

```
[0 1 0 ... 0 0 0]
Index(['Aggravated Assault', 'Ballistics', 'Vandalism', 'Homicide',
       'Warrant Arrests', 'Auto Theft', 'Drug Violation', 'Firearm Violation
s',
       'Property Found', 'Robbery', 'Police Service Incidents', 'Other',
       'Motor Vehicle Accident Response', 'Towed', 'Firearm Discovery',
       'Medical Assistance', 'Search Warrants', 'Recovered Stolen Property',
       'Investigate Person', 'Investigate Property', 'Simple Assault',
       'Disorderly Conduct', 'Property Lost', 'Violations', 'Manslaughter',
       'Property Related Damage', 'Missing Person Located'],
      dtype='object')
```

```
C:\Users\bhavs\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: UserWarni
ng: Pandas doesn't allow columns to be created via a new attribute name - see
https://pandas.pydata.org/pandas-docs/stable/indexing.html#attribute-access
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

In [29]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
rfboston['OFFENSE_CODE'] = le.fit_transform(rfboston['OFFENSE_CODE'])
```

In [30]:
```
rfboston.head()
```

Out[30]:

	INCIDENT_NUMBER	OFFENSE_CODE	OFFENSE_CODE_GROUP	OFFENSE_DESCRIPTION
876	I192077645	7	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
877	I192077645	32	Ballistics	BALLISTICS EVIDENCE/FOUND
889	I192077627	7	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
2785	I192075578	7	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
3408	I192074923	7	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY

In [31]:
```
rfboston.head() # 2 7,,,, #DEPENDENT 1
```

Out[31]:

	INCIDENT_NUMBER	OFFENSE_CODE	OFFENSE_CODE_GROUP	OFFENSE_DESCRIPTION
876	I192077645	7	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
877	I192077645	32	Ballistics	BALLISTICS EVIDENCE/FOUND
889	I192077627	7	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
2785	I192075578	7	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
3408	I192074923	7	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY

In [32]:
```
crime_data.head()
```

Out[32]:

	INCIDENT_NUMBER	OFFENSE_CODE	OFFENSE_CODE_GROUP	OFFENSE_DESCRIPTION
876	I192077645	413	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
877	I192077645	2662	Ballistics	BALLISTICS EVIDENCE/FOUND
889	I192077627	413	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
2785	I192075578	413	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY
3408	I192074923	413	Aggravated Assault	ASSAULT - AGGRAVATED - BATTERY

In [33]:
```
rfboston['OFFENSE_CODE_GROUP'] = le.fit_transform(rfboston['OFFENSE_CODE_GROUP'])
rfboston['OFFENSE_DESCRIPTION'] = le.fit_transform(rfboston['OFFENSE_DESCRIPTION'])
rfboston['DISTRICT'] = le.fit_transform(rfboston['DISTRICT'])
rfboston['INCIDENT_NUMBER'] = le.fit_transform(rfboston['INCIDENT_NUMBER'])
rfboston['UCR_PART'] = le.fit_transform(rfboston['UCR_PART'])
rfboston['SHOOTING'] = le.fit_transform(rfboston['SHOOTING'])
rfboston['OCCURRED_ON_DATE'] = le.fit_transform(rfboston['OCCURRED_ON_DATE'])
```

In [34]:
```
rfboston.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1663 entries, 876 to 426308
Data columns (total 17 columns):
INCIDENT_NUMBER        1663 non-null int32
OFFENSE_CODE           1663 non-null int64
OFFENSE_CODE_GROUP     1663 non-null int32
OFFENSE_DESCRIPTION    1663 non-null int32
DISTRICT               1663 non-null int32
REPORTING_AREA         1663 non-null object
SHOOTING               1663 non-null int32
OCCURRED_ON_DATE       1663 non-null int64
YEAR                   1663 non-null int64
MONTH                  1663 non-null int64
DAY_OF_WEEK            1663 non-null object
HOUR                   1663 non-null int64
UCR_PART               1663 non-null int32
STREET                 1663 non-null object
Lat                    1663 non-null float64
Long                   1663 non-null float64
Location               1663 non-null object
dtypes: float64(2), int32(6), int64(5), object(4)
memory usage: 194.9+ KB
```

Random Forest with Offense_Code

In [35]:
```
#Splitting the data into independent and dependent variables
X = rfboston.iloc[:,lambda df: [0,1,3,4,5,6,7,12]].values
y = rfboston.iloc[:,2].values
print('The independent features set: ')
print(X[:5,:])
print('The dependent variable: ')
print(y[:5])
```

```
The independent features set:
[[783 7 3 3 '295' 0 782 1]
 [783 32 6 3 '295' 0 782 3]
 [782 7 3 5 '344' 0 781 1]
 [781 7 3 4 '457' 0 780 1]
 [780 7 3 3 '326' 0 779 1]]
The dependent variable:
[0 2 0 0 0]
```

In [36]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, ra
ndom_state = 21)
```

In [37]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [38]:
```
classifier = RandomForestClassifier(n_estimators = 10, criterion = 'entropy',
random_state = 42)
classifier.fit(X_train, y_train)
```

Out[38]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entrop
y',
                       max_depth=None, max_features='auto', max_leaf_nodes=No
ne,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10,
                       n_jobs=None, oob_score=False, random_state=42, verbose
=0,
                       warm_start=False)
```

In [39]:
```
# Predicting the Test set results
from sklearn.metrics import accuracy_score
y_pred = classifier.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)
print("The accuracy for the above model is = ", accuracy)
```

```
The accuracy for the above model is =  0.9783653846153846
```

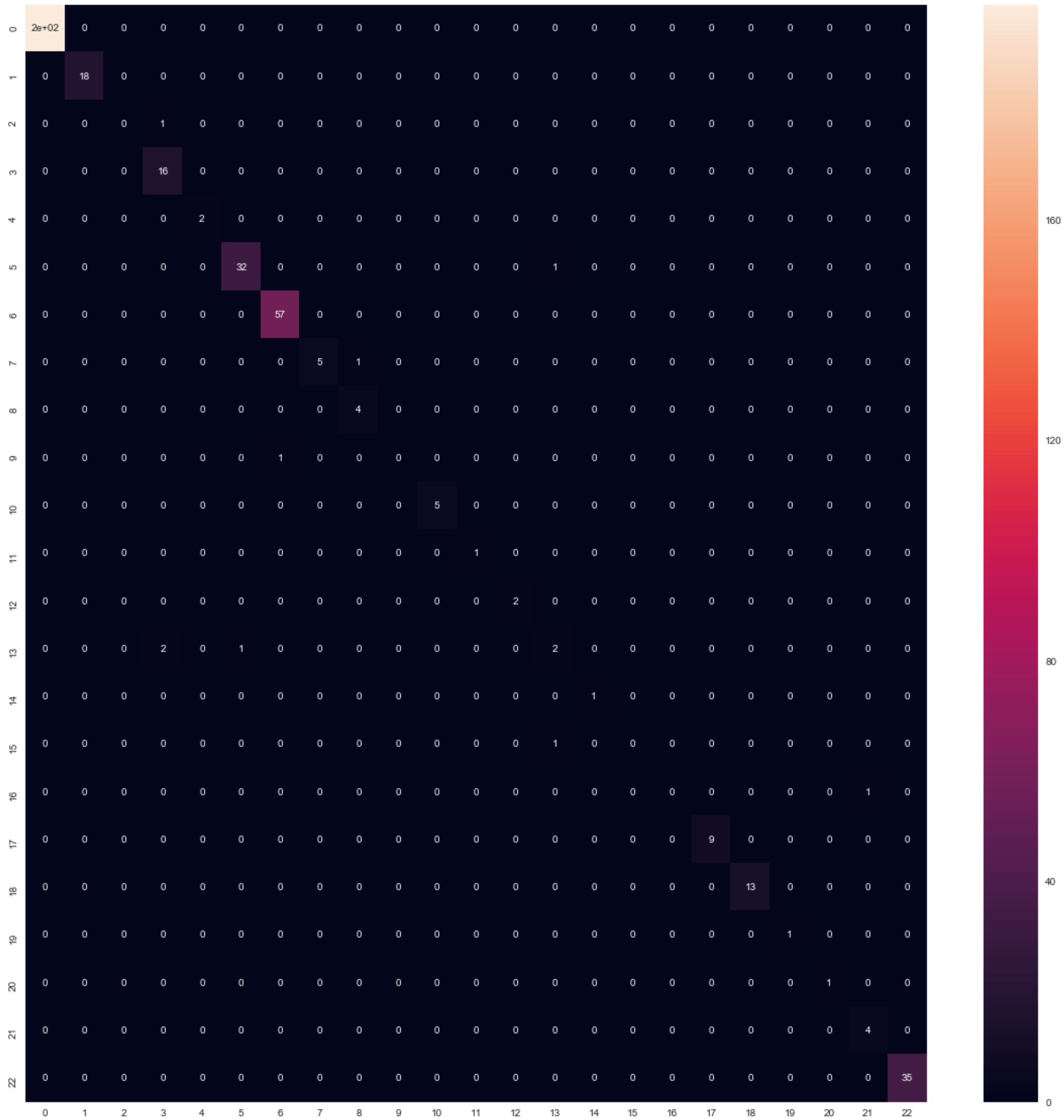
In [40]:

```
#Using scikit confusion_matrix method to determine the confusion matrix for ou
r model
#Link: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confu
sion_matrix.html#sklearn.metrics.confusion_matrix
from sklearn.metrics import confusion_matrix
print("Below is the confusion matrix for the above model")
CM = confusion_matrix(y_test, y_pred)
print(CM)
```

```
Below is the confusion matrix for the above model
[[199   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0  18   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0  16   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   2   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0  32   0   0   0   0   0   0   0   1   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0  57   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   5   1   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   4   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   5   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   1   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   2   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   2   0   1   0   0   0   0   0   0   0   2   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   1   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   9
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   13   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   1   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   1   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   4   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0  35]]
```

In [41]:
```
df_cm = pd.DataFrame(CM, index = [i for i in range(23)],
                     columns = [i for i in range(23)])
plt.figure(figsize = (20,20))
sns.heatmap(df_cm, annot=True)
```

Out[41]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x24aa5a5ac50>
```



Random Forest without Offense_Code

In [42]:
```
#Splitting the data into independent and dependent variables
X_2 = rfboston.iloc[:,lambda df: [0,3,4,5,6,7,12]].values
y_2 = rfboston.iloc[:,2].values
print('The independent features set: ')
print(X_2[:5,:])
print('The dependent variable: ')
print(y_2[:5])
```

```
The independent features set:
[[783 3 3 '295' 0 782 1]
 [783 6 3 '295' 0 782 3]
 [782 3 5 '344' 0 781 1]
 [781 3 4 '457' 0 780 1]
 [780 3 3 '326' 0 779 1]]
The dependent variable:
[0 2 0 0 0]
```

In [43]:
```
X_2_train, X_2_test, y_2_train, y_2_test = train_test_split(X_2, y_2, test_siz
e = 0.25, random_state = 21)
```

In [44]:
```
scaler = StandardScaler()
X_2_train = scaler.fit_transform(X_2_train)
X_2_test = scaler.transform(X_2_test)
```

In [45]:
```
# Fitting Random Forest Classification to the Training set
classifier = RandomForestClassifier(n_estimators = 10, criterion = 'entropy',
random_state = 42)
classifier.fit(X_2_train, y_2_train)
```

Out[45]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entrop
y',
                       max_depth=None, max_features='auto', max_leaf_nodes=No
ne,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10,
                       n_jobs=None, oob_score=False, random_state=42, verbose
=0,
                       warm_start=False)
```

In [46]:
```
# Predicting the Test set results
from sklearn.metrics import accuracy_score
y_2_pred = classifier.predict(X_2_test)

accuracy = accuracy_score(y_2_test, y_2_pred)
print("The accuracy for the above model is = ", accuracy)
```

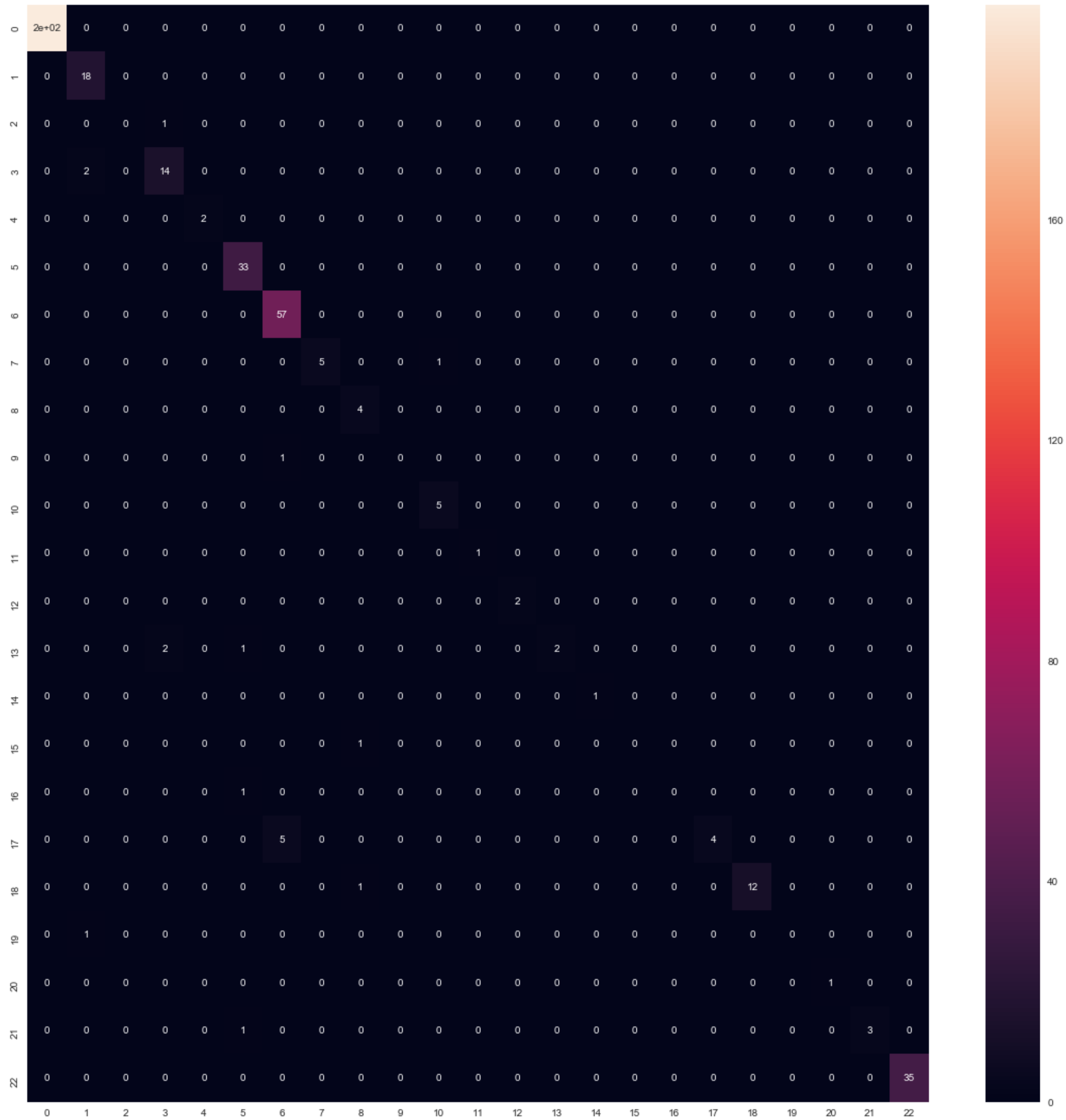
```
The accuracy for the above model is =  0.9567307692307693
```

In [47]:
```
#Using scikit confusion_matrix method to determine the confusion matrix for ou
r model
#Link: https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confu
sion_matrix.html#sklearn.metrics.confusion_matrix
#from sklearn.metrics import confusion_matrix
print("Below is the confusion matrix for the above model")
CM2 = confusion_matrix(y_2_test, y_2_pred)
print(CM2)
```

```
Below is the confusion matrix for the above model
[[199   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0  18   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   2   0  14   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   2   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0  33   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0  57   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   5   0   0   1   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   4   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   5   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   1   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   2   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   2   0   1   0   0   0   0   0   0   0   2   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   1   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   5   0   0   0   0   0   0   0   0   0   0   4
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0
   12   0   0   0   0]
 [  0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   1   0   0]
 [  0   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   3   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0  35]]
```

In [48]:
```
df_cm2 = pd.DataFrame(CM2, index = [i for i in range(23)],
                      columns = [i for i in range(23)])
plt.figure(figsize = (20,20))
sns.heatmap(df_cm2, annot=True)
```

Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x24aa5af7208>



Random Forest 3 : Dataset without the Offense_code and Offense_Description

In [49]:
```
#Splitting the data into independent and dependent variables
X_3 = rfboston.iloc[:,lambda df: [0,4,5,6,7,12]].values
y_3 = rfboston.iloc[:,2].values
print('The independent features set: ')
print(X_3[:5,:])
print('The dependent variable: ')
print(y_3[:5])
```

```
The independent features set:
[[783 3 '295' 0 782 1]
 [783 3 '295' 0 782 3]
 [782 5 '344' 0 781 1]
 [781 4 '457' 0 780 1]
 [780 3 '326' 0 779 1]]
The dependent variable:
[0 2 0 0 0]
```

In [50]:
```
X_3_train, X_3_test, y_3_train, y_3_test = train_test_split(X_3, y_3, test_siz
e = 0.25, random_state = 21)
```

In [51]:
```
# Feature Scaling
scaler = StandardScaler()
X_3_train = scaler.fit_transform(X_3_train)
X_3_test = scaler.transform(X_3_test)
```

In [52]:
```
# Fitting Random Forest Classification to the Training set
classifier = RandomForestClassifier(n_estimators = 10, criterion = 'entropy',
random_state = 42)
classifier.fit(X_3_train, y_3_train)
```

Out[52]:
```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entrop
y',
                       max_depth=None, max_features='auto', max_leaf_nodes=No
ne,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=10,
                       n_jobs=None, oob_score=False, random_state=42, verbose
=0,
                       warm_start=False)
```

In [53]:
```
# Predicting the Test set results
from sklearn.metrics import accuracy_score
y_3_pred = classifier.predict(X_3_test)

accuracy = accuracy_score(y_3_test, y_3_pred)
print("The accuracy for the above model is = ", accuracy)
```

```
The accuracy for the above model is =  0.6105769230769231
```

Metrics for Random forest model

1. F1 Score

In [54]:
```
from sklearn.metrics import f1_score
f1_score(y_2_test, y_2_pred, average='weighted')
```

```
C:\Users\bhavs\Anaconda3\lib\site-packages\sklearn\metrics\classification.py:
1437: UndefinedMetricWarning: F-score is ill-defined and being set to 0.0 in
labels with no predicted samples.
  'precision', 'predicted', average, warn_for)
```

Out[54]:
```
0.9481022485736115
```

1. Root Mean Squared Error

In [55]:
```
from sklearn.metrics import mean_squared_error
from math import sqrt

rms = sqrt(mean_squared_error(y_2_test, y_2_pred))
rms
```

Out[55]:
```
2.318922992717491
```

Time Series Model

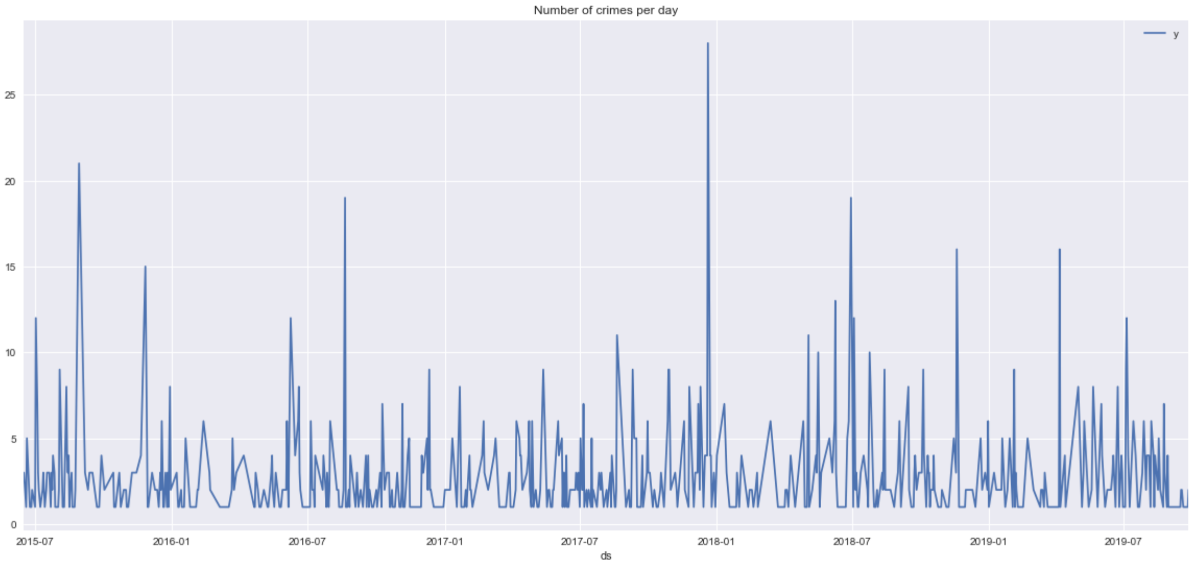
In [56]:
```
crime_data['Date Only'] = crime_data['OCCURRED_ON_DATE'].dt.date
#timeSeries = chi.groupby('Date').count()
```

In [57]:
```
timeSeries = crime_data.groupby('Date Only').count()['OFFENSE_CODE_GROUP'].to_
frame()
timeSeries.reset_index(inplace=True)
timeSeries.columns = ['ds','y']
timeSeries.head()
```

Out[57]:

	ds	y
0	2015-06-16	3
1	2015-06-19	1
2	2015-06-20	5
3	2015-06-24	1
4	2015-06-25	1

In [58]:
```
timeSeries.plot(x='ds', title='Number of crimes per day')
plt.show()
```



In [59]:
```
prophet_ds = timeSeries.copy()
```

In [60]:
```
prophet_ds.head()
```

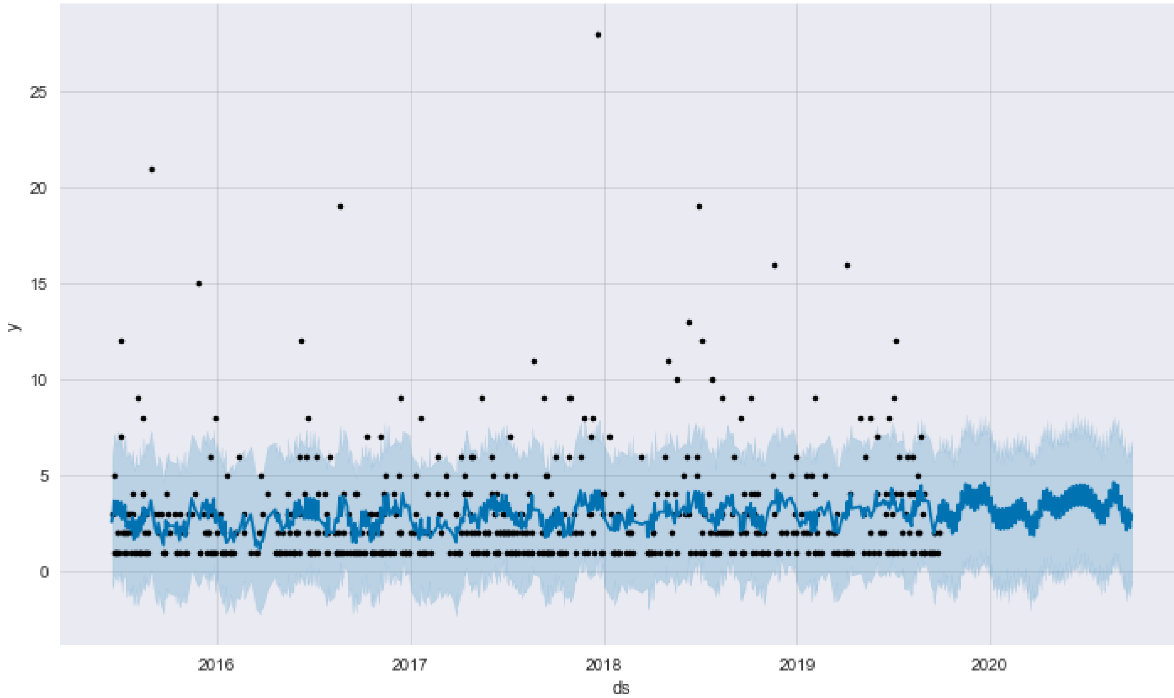
Out[60]:

	ds	y
0	2015-06-16	3
1	2015-06-19	1
2	2015-06-20	5
3	2015-06-24	1
4	2015-06-25	1

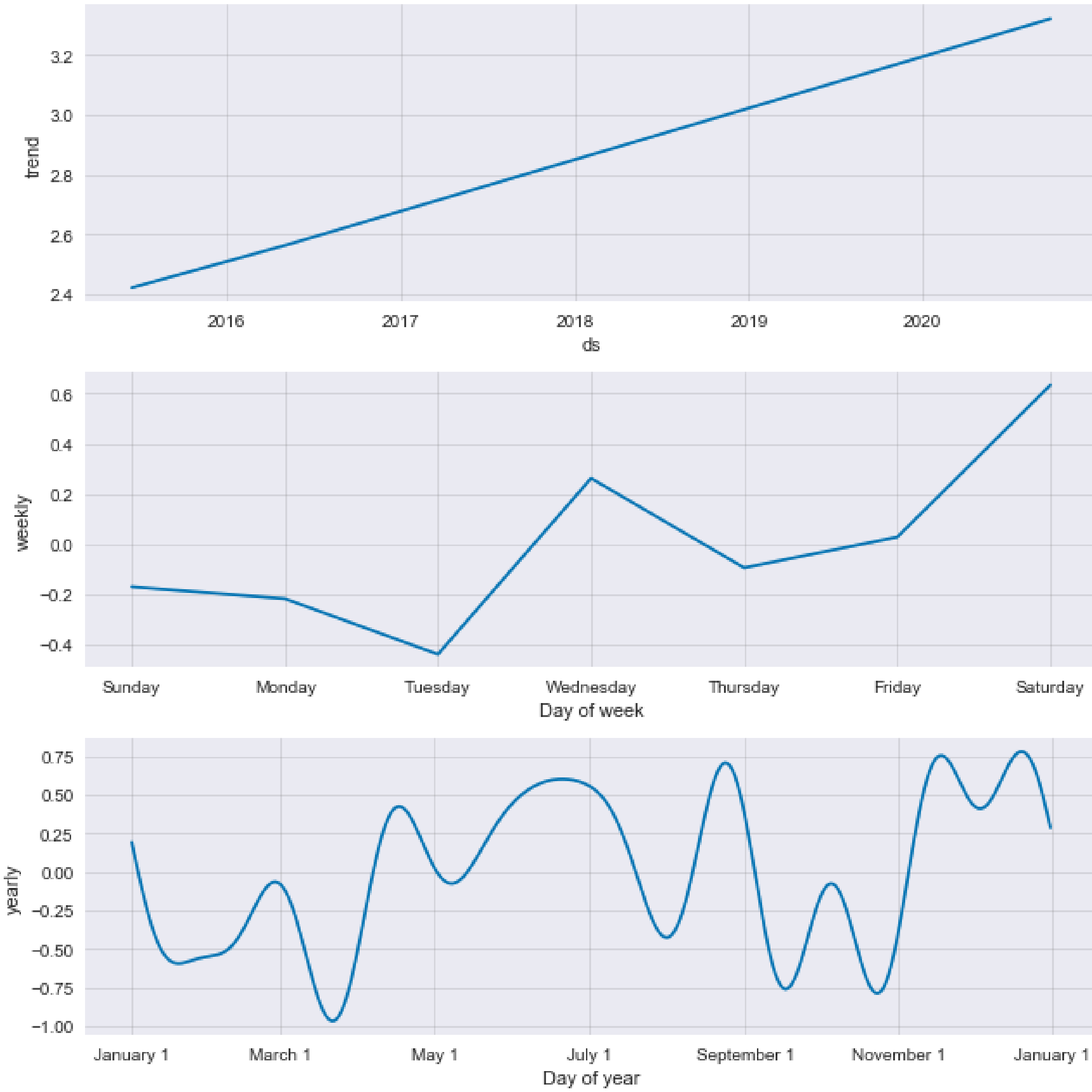
In [61]:
```
from fbprophet import Prophet

# Prophet code are basically these lines
prophet_model = Prophet()
prophet_model.fit(prophet_ds)

# Let's try a forecast for 365 days
future = prophet_model.make_future_dataframe(periods=365)
forecast_df = prophet_model.predict(future)
```

```
ERROR:fbprophet:Importing plotly failed. Interactive plots will not work.
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonalit
y=True to override this.
```

In [62]:
```
ts_plot = prophet_model.plot(forecast_df)
```



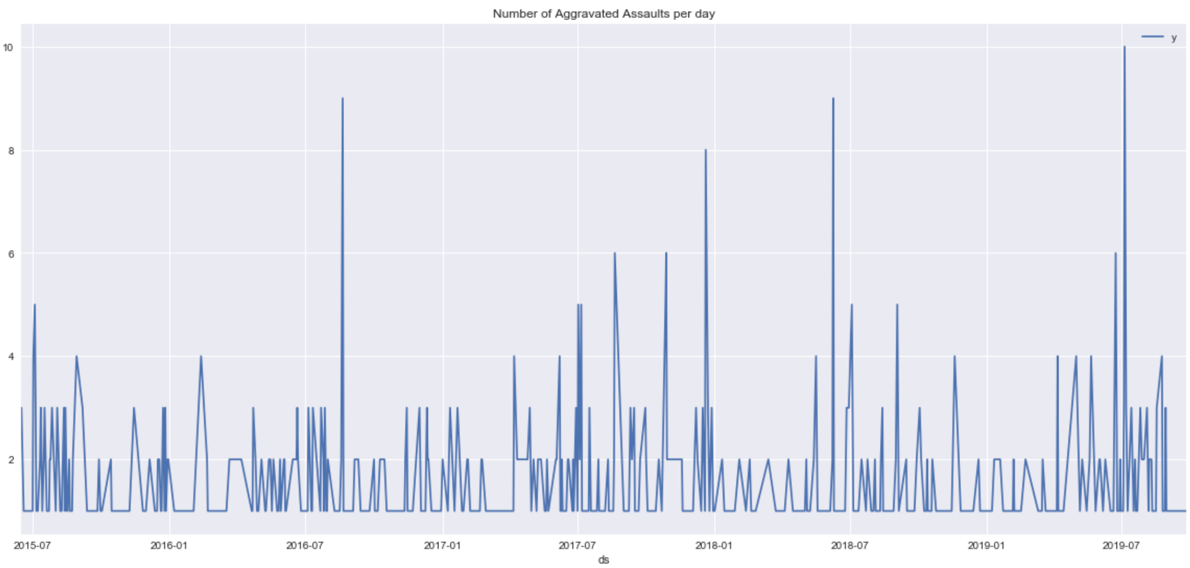
In [63]:
```
PC = prophet_model.plot_components(forecast_df)
```



In [64]:
```
#filtering out the arson from other crime types and then applying time series
 model
assault = crime_data[crime_data['OFFENSE_CODE_GROUP'] == 'Aggravated Assault']
assault['Date Only'] = assault['OCCURRED_ON_DATE'].dt.date
```

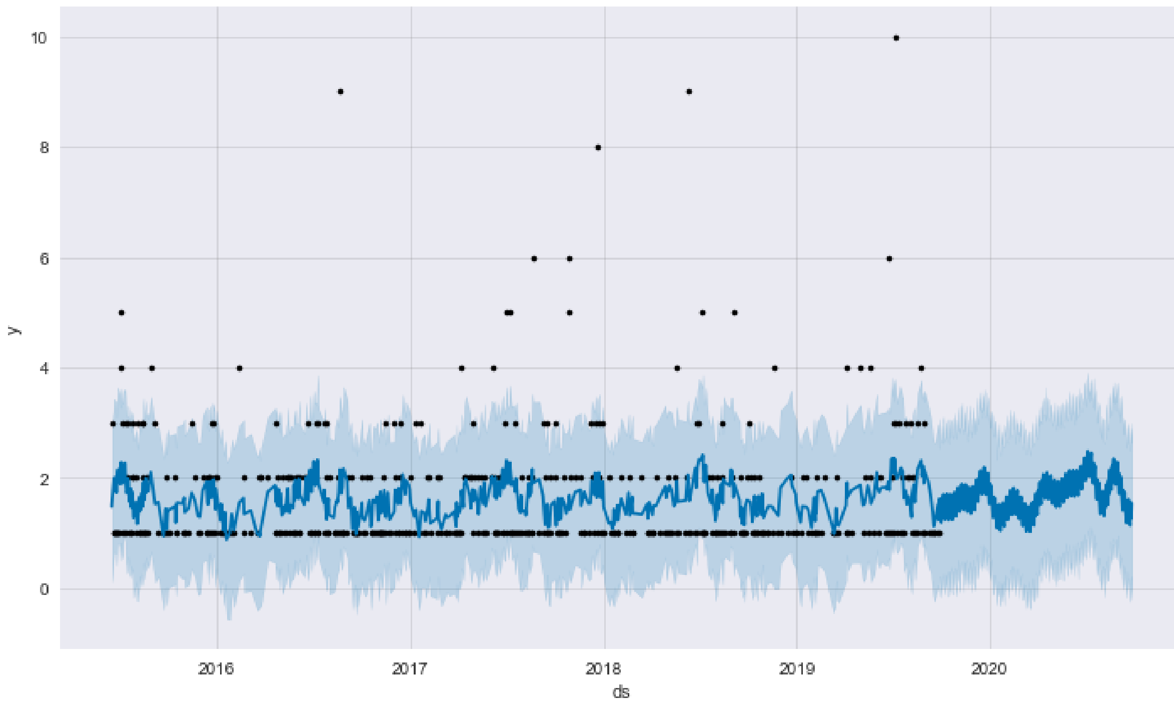
```
C:\Users\bhavs\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

In [65]:
```
ts_assault = assault.groupby('Date Only').count()['OFFENSE_CODE_GROUP'].to_frame()
ts_assault.reset_index(inplace=True)
ts_assault.columns = ['ds','y']
ts_assault.plot(x='ds', title='Number of Aggravated Assaults per day')
plt.show()
```

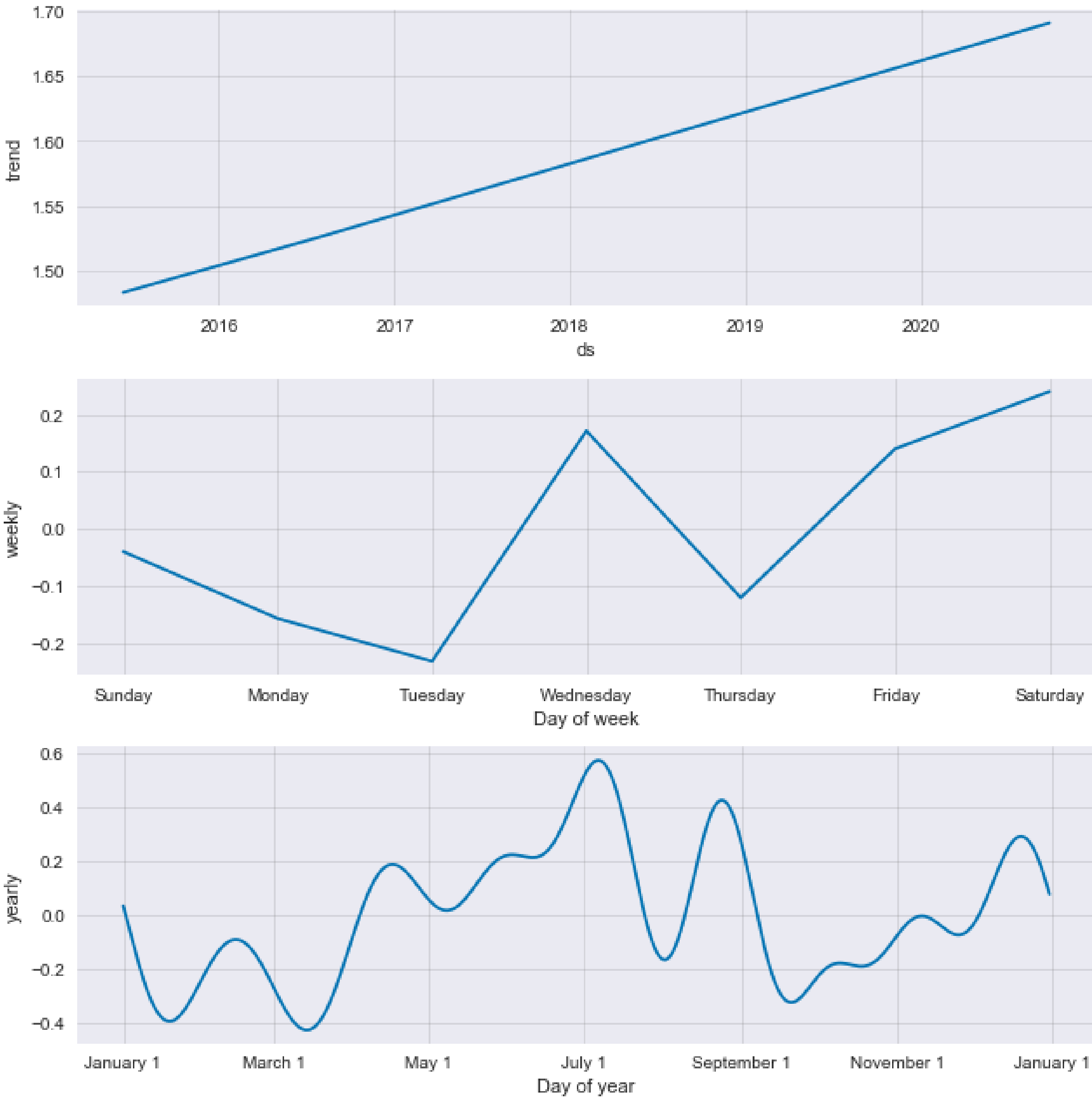


In [66]:
```
prophet_assault = ts_assault.copy()
prophet_model = Prophet()
prophet_model.fit(prophet_assault)

# Let's try a forecast for 365 days
future = prophet_model.make_future_dataframe(periods=365)
forecast_df = prophet_model.predict(future)
ts_assault = prophet_model.plot(forecast_df)
```

```
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonalit
y=True to override this.
```

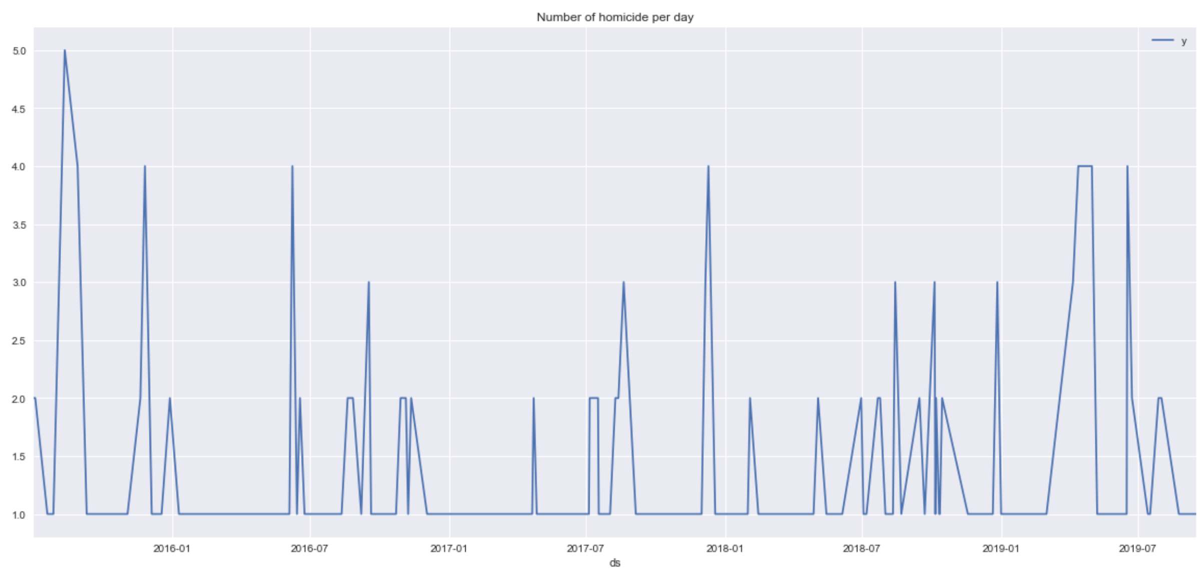


In [67]:
```
PC = prophet_model.plot_components(forecast_df)
```



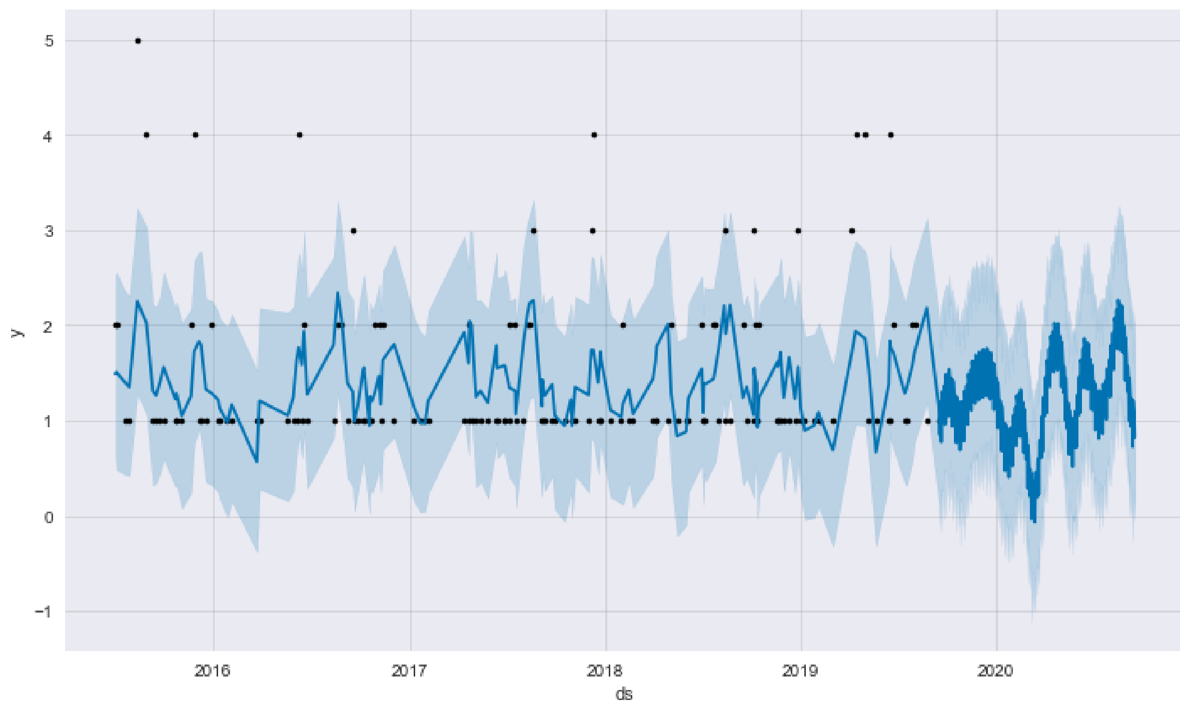
In [68]:
```
#filtering out the assault from other crime types and then applying time serie
s model
homicide = crime_data[crime_data['OFFENSE_CODE_GROUP'] == 'Homicide']
homicide['Date Only'] = homicide['OCCURRED_ON_DATE'].dt.date
ts_homicide = homicide.groupby('Date Only').count()['OFFENSE_CODE_GROUP'].to_f
rame()
ts_homicide.reset_index(inplace=True)
ts_homicide.columns = ['ds','y']
ts_homicide.plot(x='ds', title='Number of homicide per day')
plt.show()
```

```
C:\Users\bhavs\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

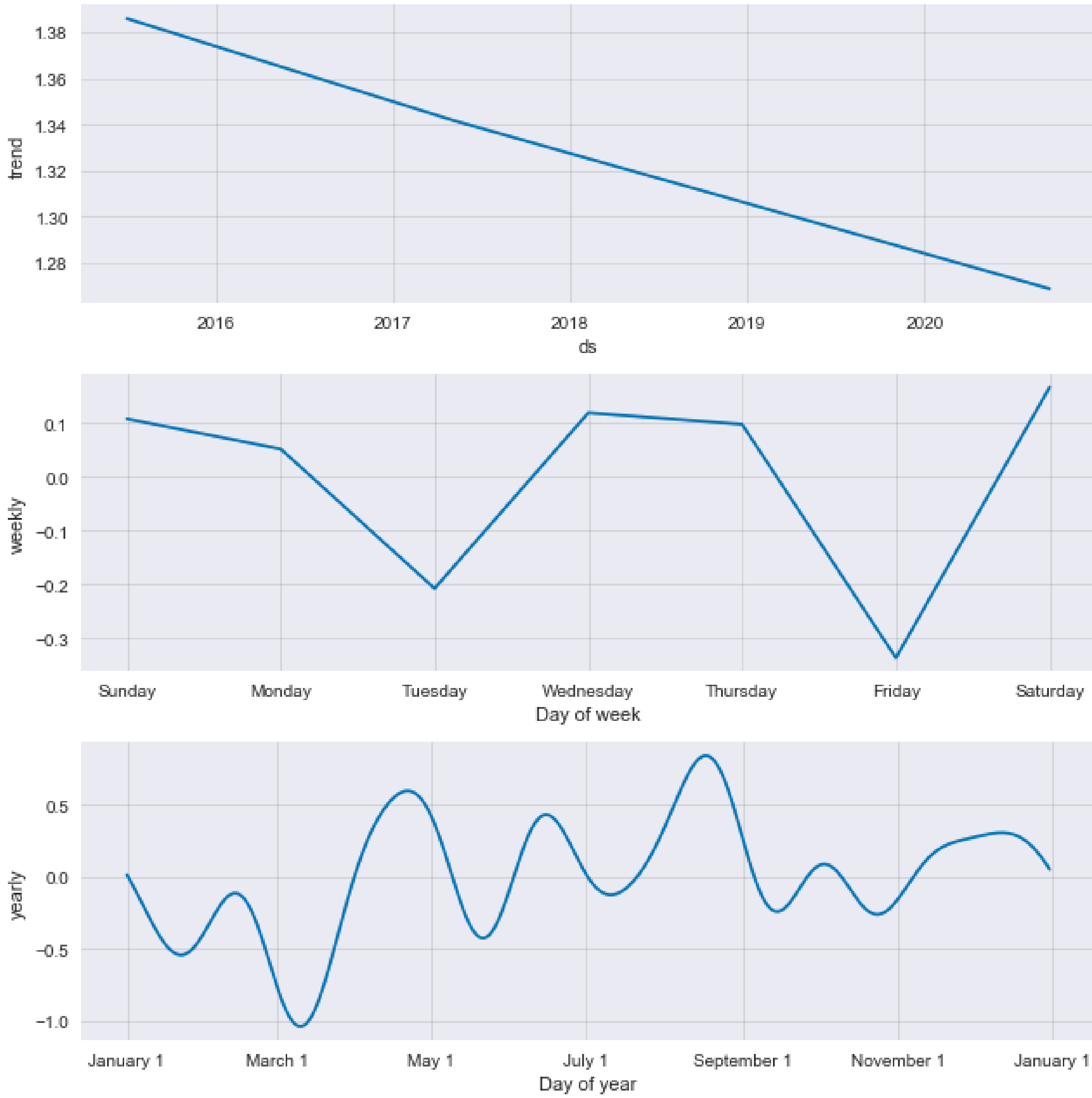


In [69]:
```
prophet_homicide = ts_homicide.copy()
prophet_model = Prophet()
prophet_model.fit(prophet_homicide)

# Let's try a forecast for 365 days
future = prophet_model.make_future_dataframe(periods=365)
forecast_df = prophet_model.predict(future)
ts_assault = prophet_model.plot(forecast_df)
```

```
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonalit
y=True to override this.
```

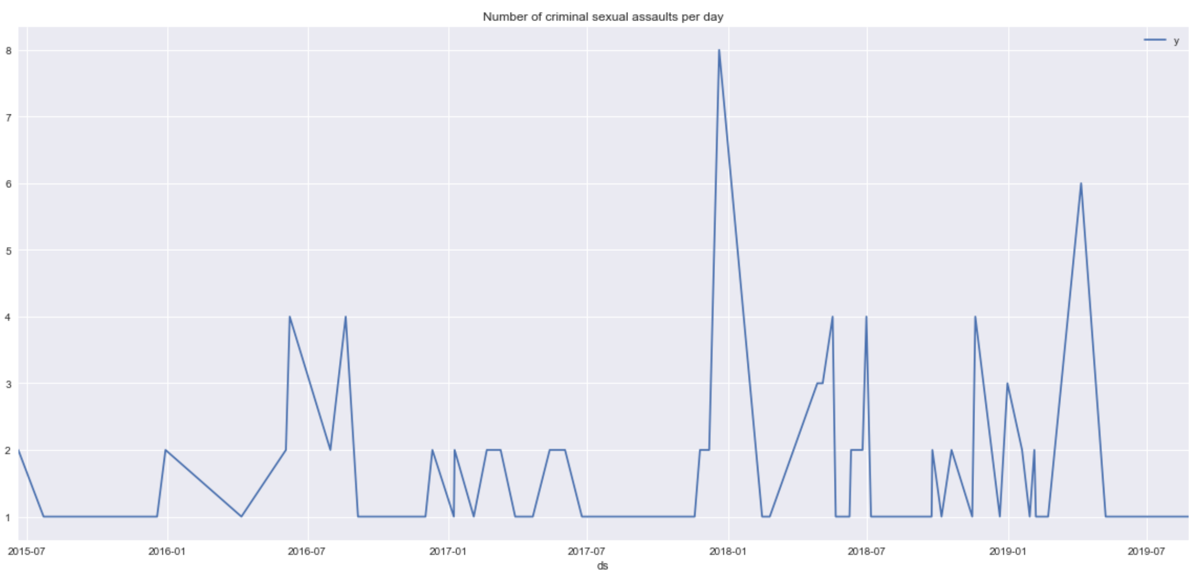


In [70]:
```
PC = prophet_model.plot_components(forecast_df)
```



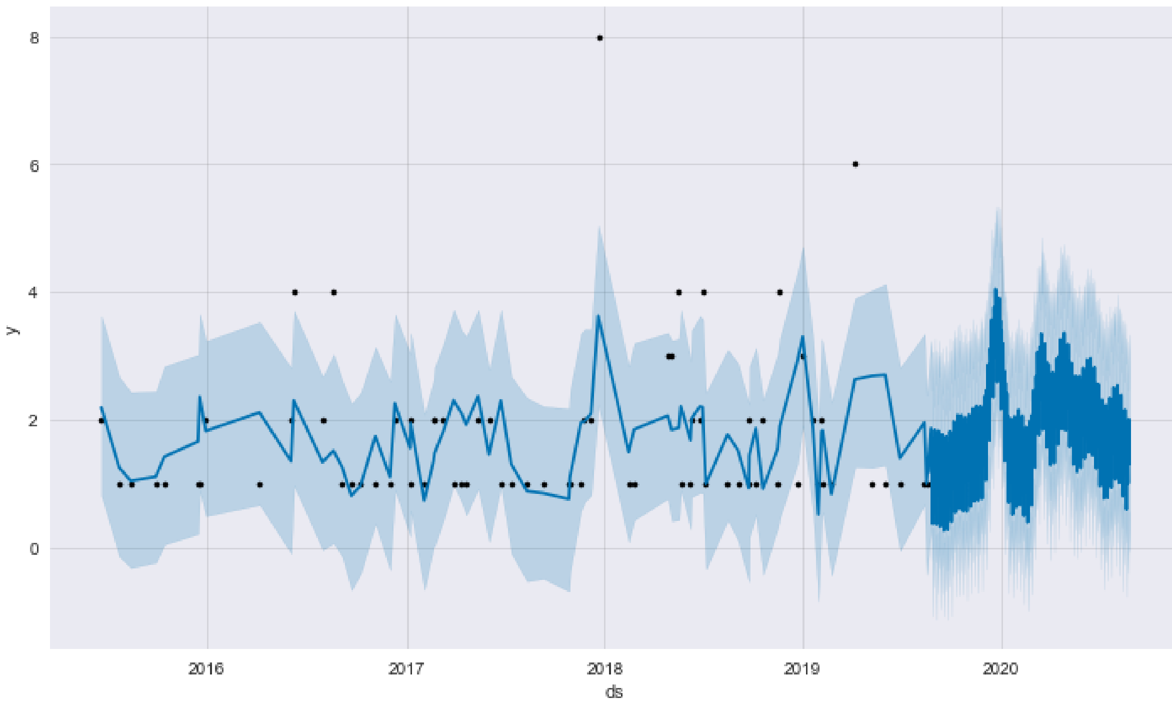
In [71]:
```
#filtering out the criminal sexual assault from other crime types and then app
lying time series model
firearm_violations = crime_data[crime_data['OFFENSE_CODE_GROUP'] == 'Firearm V
iolations']
firearm_violations['Date Only'] = firearm_violations['OCCURRED_ON_DATE'].dt.da
te
ts_firearm_violations = firearm_violations.groupby('Date Only').count()['OFFEN
SE_CODE_GROUP'].to_frame()
ts_firearm_violations.reset_index(inplace=True)
ts_firearm_violations.columns = ['ds','y']
ts_firearm_violations.plot(x='ds', title='Number of criminal sexual assaults p
er day')
plt.show()
```

```
C:\Users\bhavs\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

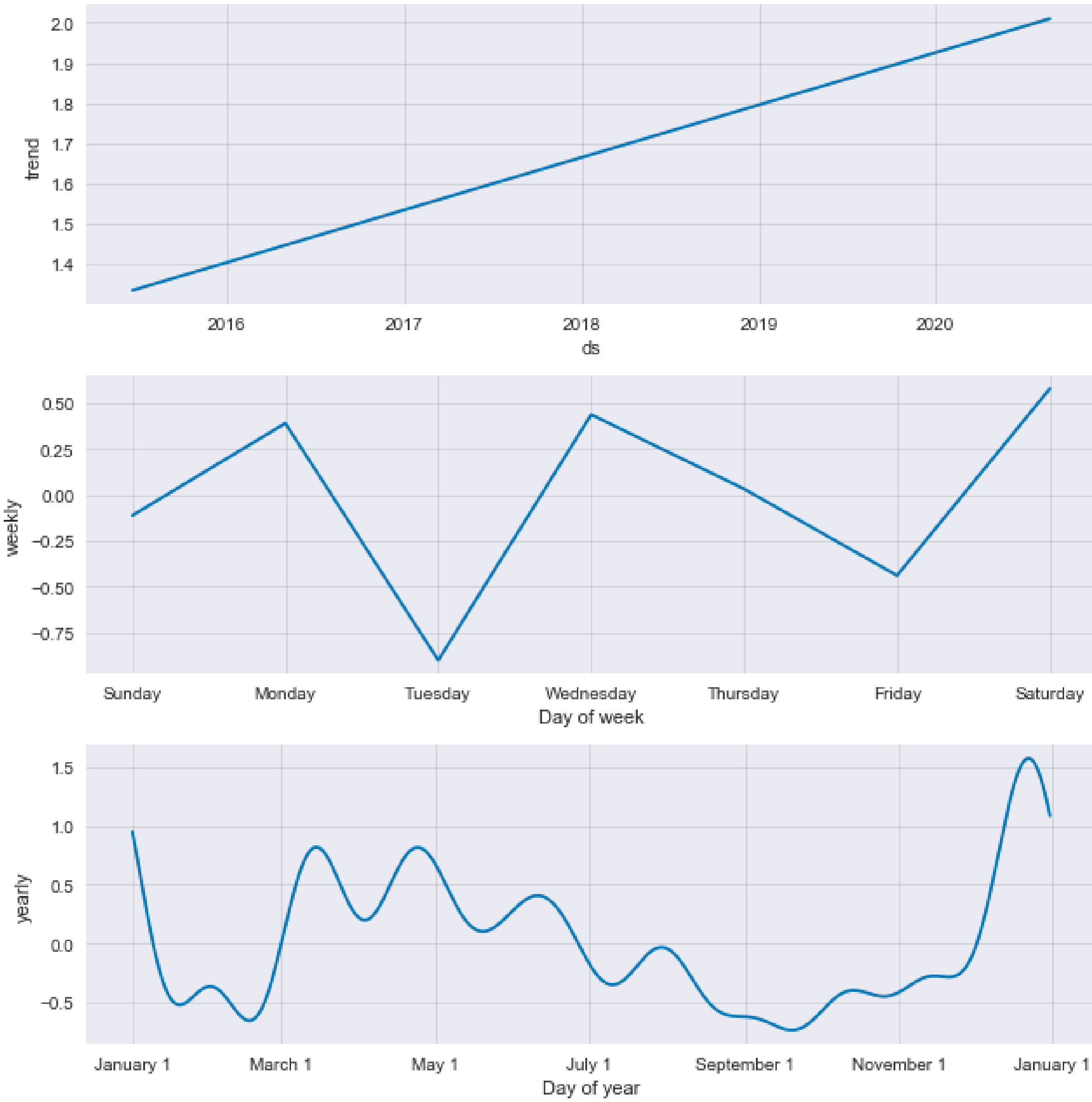


In [72]:
```
prophet_firearm_violations = ts_firearm_violations.copy()
prophet_model = Prophet()
prophet_model.fit(prophet_firearm_violations)

# Let's try a forecast for 365 days
future = prophet_model.make_future_dataframe(periods=365)
forecast_df = prophet_model.predict(future)
ts_assault = prophet_model.plot(forecast_df)
```

```
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonalit
y=True to override this.
```

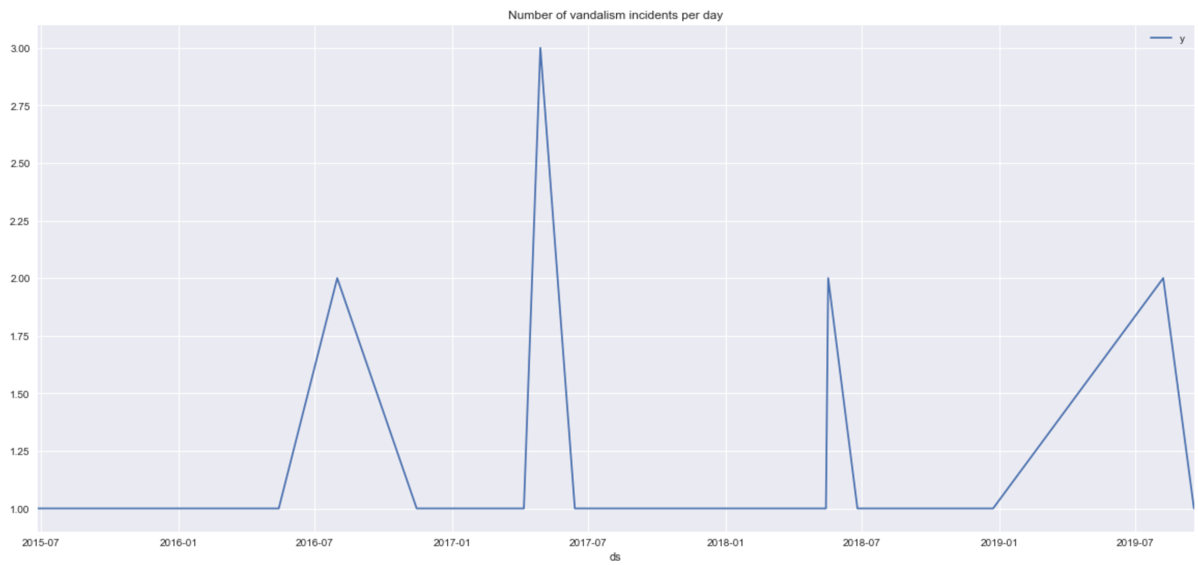


In [73]:
```
PC = prophet_model.plot_components(forecast_df)
```



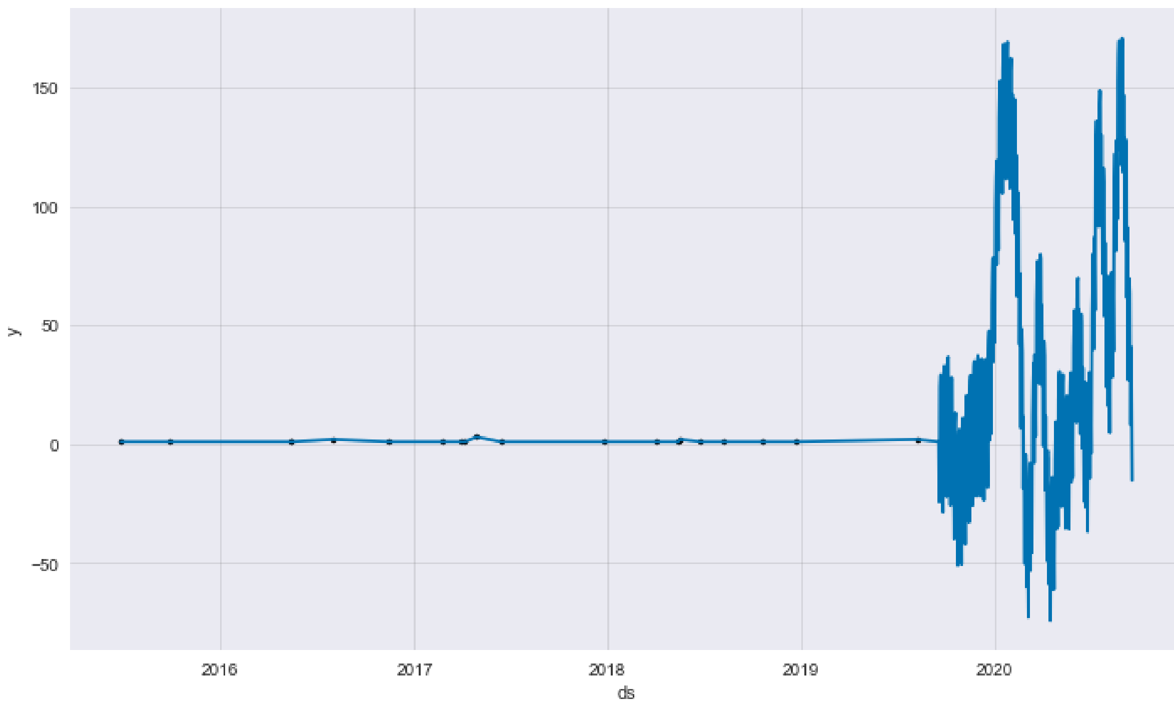
In [74]:
```
#filtering out the criminal sexual assault from other crime types and then app
lying time series model
vandalism = crime_data[crime_data['OFFENSE_CODE_GROUP'] == 'Vandalism']
vandalism['Date Only'] = vandalism['OCCURRED_ON_DATE'].dt.date
ts_vandalism = vandalism.groupby('Date Only').count()['OFFENSE_CODE_GROUP'].to
_frame()
ts_vandalism.reset_index(inplace=True)
ts_vandalism.columns = ['ds','y']
ts_vandalism.plot(x='ds', title='Number of vandalism incidents per day')
plt.show()
```

```
C:\Users\bhavs\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

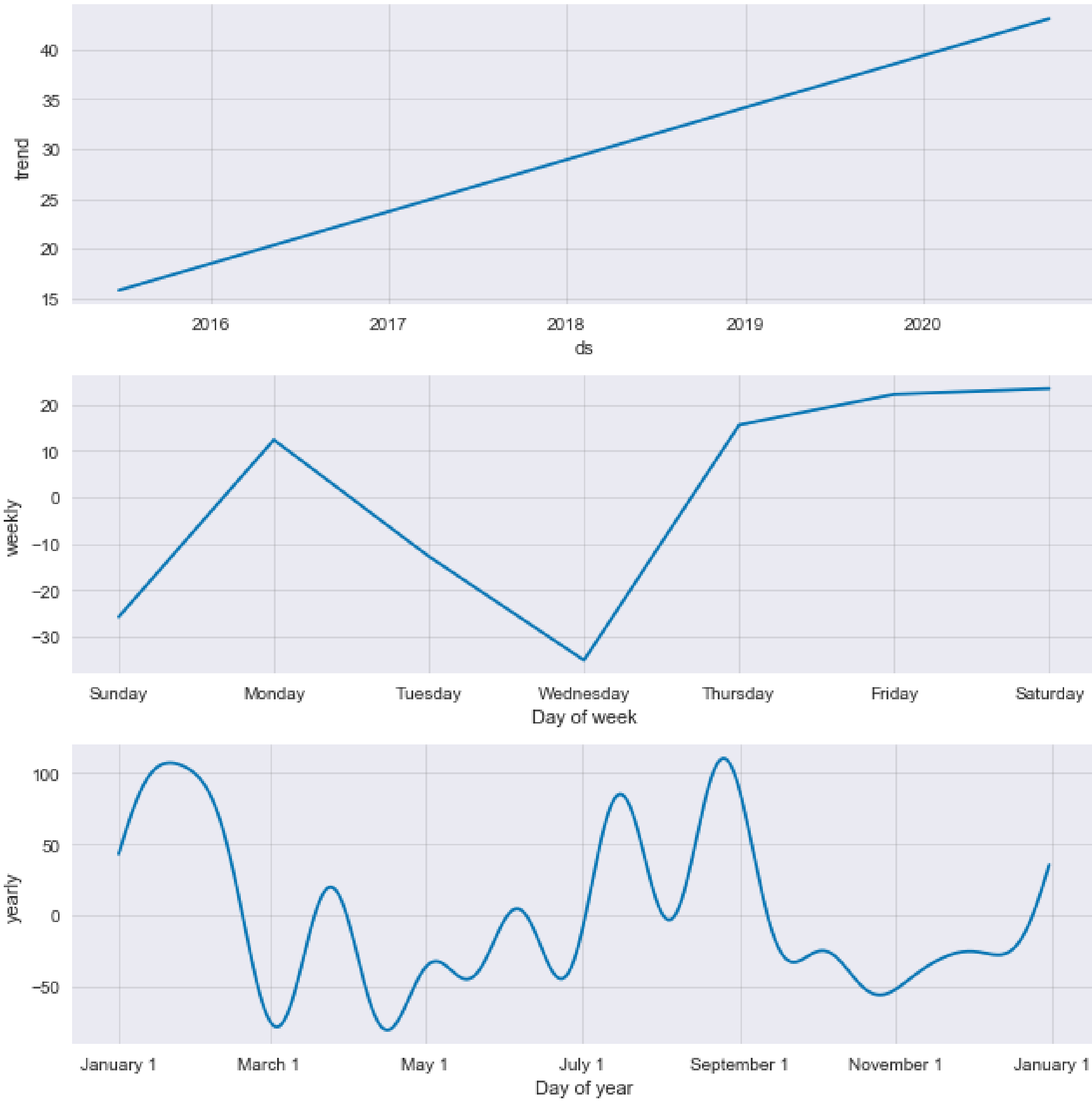


In [75]:
```
prophet_vandalism = ts_vandalism.copy()
prophet_model = Prophet()
prophet_model.fit(prophet_vandalism)

# Let's try a forecast for 365 days
future = prophet_model.make_future_dataframe(periods=365)
forecast_df = prophet_model.predict(future)
ts_assault = prophet_model.plot(forecast_df)
```

```
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonalit
y=True to override this.
INFO:fbprophet:n_changepoints greater than number of observations.Using 15.
```

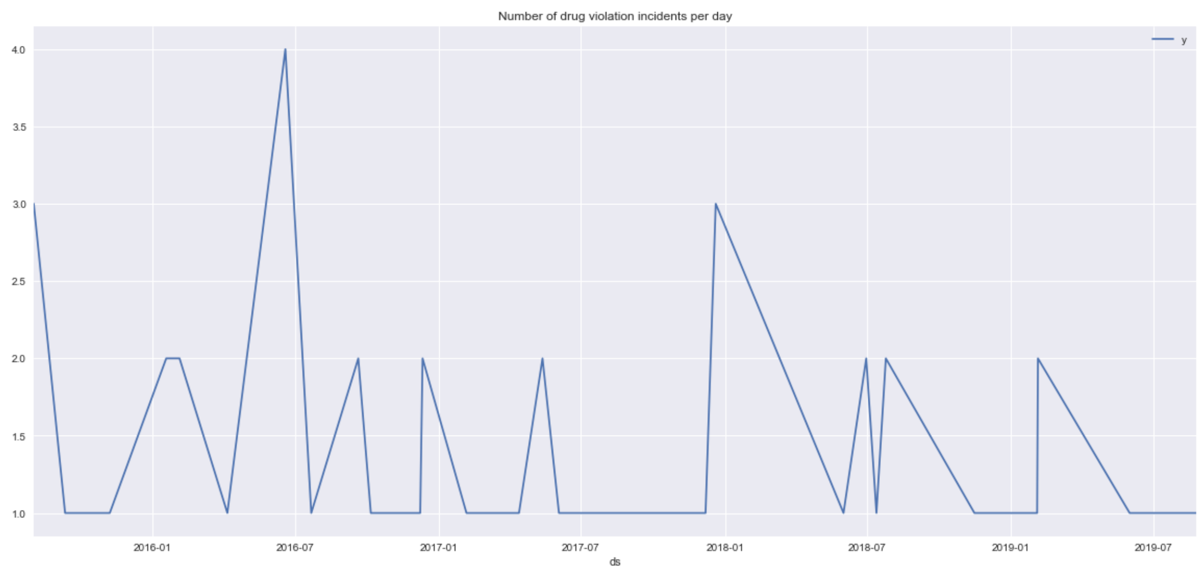


In [76]:
```
PC = prophet_model.plot_components(forecast_df)
```



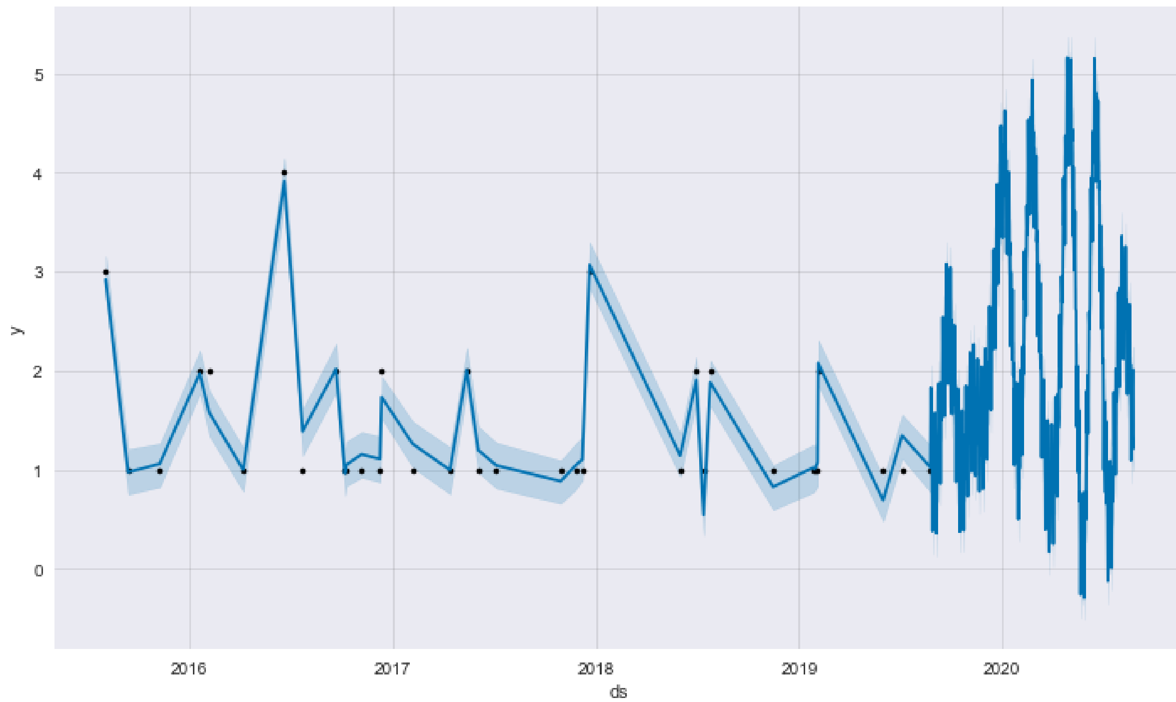
In [77]:
```
#filtering out the criminal sexual assault from other crime types and then app
lying time series model
drug_violation = crime_data[crime_data['OFFENSE_CODE_GROUP'] == 'Drug Violatio
n']
drug_violation['Date Only'] = drug_violation['OCCURRED_ON_DATE'].dt.date
ts_drug_violation = drug_violation.groupby('Date Only').count()['OFFENSE_CODE_
GROUP'].to_frame()
ts_drug_violation.reset_index(inplace=True)
ts_drug_violation.columns = ['ds','y']
ts_drug_violation.plot(x='ds', title='Number of drug violation incidents per d
ay')
plt.show()
```

```
C:\Users\bhavs\Anaconda3\lib\site-packages\ipykernel_launcher.py:3: SettingWi
thCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/st
able/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing imports u
ntil
```

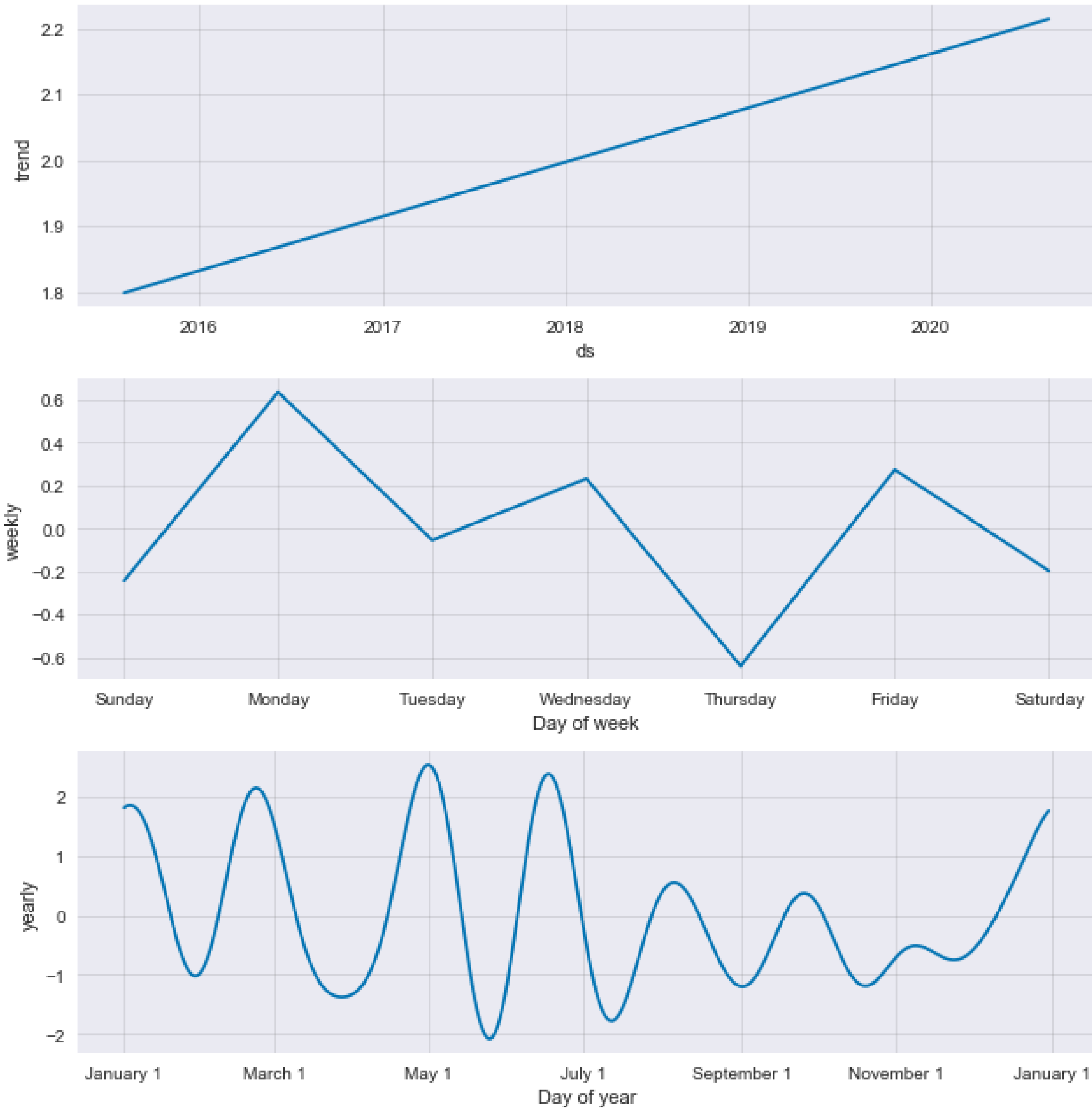


In [78]:
```
prophet_drug_violation = ts_drug_violation.copy()
prophet_model = Prophet()
prophet_model.fit(prophet_drug_violation)

# Let's try a forecast for 365 days
future = prophet_model.make_future_dataframe(periods=365)
forecast_df = prophet_model.predict(future)
ts_assault = prophet_model.plot(forecast_df)
```

```
INFO:fbprophet:Disabling daily seasonality. Run prophet with daily_seasonalit
y=True to override this.
```



In [79]:
```
PC = prophet_model.plot_components(forecast_df)
```



In [80]:
```
forecast_df.head()
```

Out[80]:

	ds	trend	yhat_lower	yhat_upper	trend_lower	trend_upper	additive_terms	additive_te
0	2015-08-03	1.798605	2.729513	3.160346	1.798605	1.798605	1.123229	
1	2015-09-12	1.807598	0.752294	1.210353	1.807598	1.807598	-0.831737	
2	2015-11-08	1.820413	0.826354	1.267532	1.820413	1.820413	-0.759829	
3	2016-01-19	1.836600	1.770995	2.206981	1.836600	1.836600	0.138492	
4	2016-02-05	1.840422	1.339196	1.799558	1.840422	1.840422	-0.262719	

Time Series Metrics

In [81]:
```
from fbprophet.diagnostics import cross_validation
df_cv = cross_validation(prophet_model, initial='730 days', period='90 days',
horizon = '365 days')
df_cv.head()
```

```
INFO:fbprophet:Making 5 forecasts with cutoffs between 2017-08-30 00:00:00 an
d 2018-08-25 00:00:00
INFO:fbprophet:n_changepoints greater than number of observations.Using 14.
INFO:fbprophet:n_changepoints greater than number of observations.Using 15.
INFO:fbprophet:n_changepoints greater than number of observations.Using 17.
INFO:fbprophet:n_changepoints greater than number of observations.Using 17.
INFO:fbprophet:n_changepoints greater than number of observations.Using 20.
```

Out[81]:

	ds	yhat	yhat_lower	yhat_upper	y	cutoff
0	2017-10-29	4.518202	4.518197	4.518206	1	2017-08-30
1	2017-11-25	-14.321981	-14.321988	-14.321975	1	2017-08-30
2	2017-12-07	-1.157371	-1.157378	-1.157364	1	2017-08-30
3	2017-12-20	-39.245883	-39.245891	-39.245875	3	2017-08-30
4	2018-06-01	2.426006	2.425983	2.426028	1	2017-08-30

In [82]:
```
from fbprophet.diagnostics import performance_metrics
df_p = performance_metrics(df_cv)
df_p.head()
```

Out[82]:

	horizon	mse	rmse	mae	mape	coverage
0	34 days	87.640184	9.361634	6.505823	2.939213	0.0
1	47 days	90.389711	9.507350	7.065447	3.498837	0.0
2	59 days	91.915978	9.587282	7.346971	3.371141	0.0
3	60 days	14.156357	3.762493	3.730577	2.752043	0.0
4	82 days	21.710840	4.659489	4.376633	3.967412	0.0

In [83]:
```
from fbprophet.plot import plot_cross_validation_metric
fig = plot_cross_validation_metric(df_cv, metric='rmse')
```