Customer Service Request Analysis using Python

By Nishit Kothari (User I.D. 205453)

In [2]:

```
#Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
plt.style.use(['fivethirtyeight'])
plt.rcParams['lines.linewidth'] = 3
import warnings
warnings.filterwarnings('ignore')
import scipy.stats as stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

Import the NYC 311 dataset

In [3]:

```
#Load the dataset
df = pd.read_csv('311_Service_Requests_from_2010_to_Present.csv', header=0, sep=',', parse_dates=['Created Date', 'Cl
```

Convert the columns 'Created Date' and 'Closed Date' to datetime datatype and create a new column 'Request_Closing_Time'

In [4]:

```
#Prepare data
def prepareData(df):
    df['Resolution_Time'] = (df['Closed Date']-df['Created Date']).dt.total_seconds()##days/3600
    df_clean=df[df['Resolution_Time'].notnull()]
    df_perfect = df_clean[df_clean['Closed Date'] >= df_clean['Created Date']]
    df_perfect['Day of Week'] = df_perfect['Created Date'].dt.dayofweek
    df_perfect['Day of Month'] = df_perfect['Created Date'].dt.day
    df_perfect['Month'] = df_perfect['Created Date'].dt.month
```

```
    df_perfect['Year'] = df_perfect['Created Date'].dt.year
    df_perfect = df_perfect[df_perfect.Borough!='Unspecified']
    return df_perfect
```

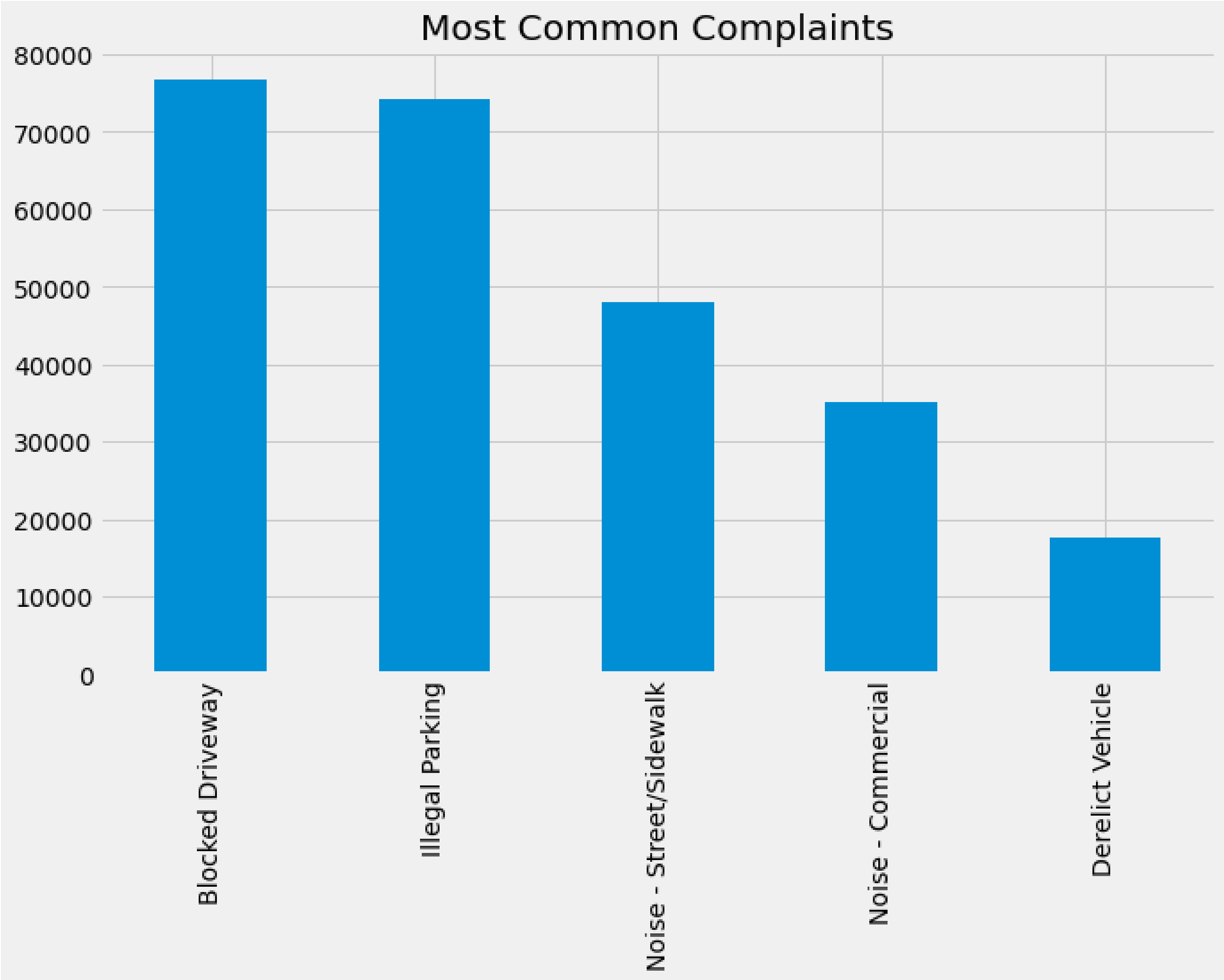
In [5]:
```
#shape
df_perfect = prepareData(df)
df_perfect.shape
df_perfect.columns
```

Out[5]:
```
Index(['Created Date', 'Closed Date', 'Agency', 'Agency Name',
       'Complaint Type', 'Descriptor', 'Location Type', 'Incident Zip',
       'Incident Address', 'Street Name', 'Cross Street 1', 'Cross Street 2',
       'Intersection Street 1', 'Intersection Street 2', 'Address Type',
       'City', 'Landmark', 'Facility Type', 'Status', 'Due Date',
       'Resolution Description', 'Resolution Action Updated Date',
       'Community Board', 'Borough', 'X Coordinate (State Plane)',
       'Y Coordinate (State Plane)', 'Park Facility Name', 'Park Borough',
       'School Name', 'School Number', 'School Region', 'School Code',
       'School Phone Number', 'School Address', 'School City', 'School State',
       'School Zip', 'School Not Found', 'School or Citywide Complaint',
       'Vehicle Type', 'Taxi Company Borough', 'Taxi Pick Up Location',
       'Bridge Highway Name', 'Bridge Highway Direction', 'Road Ramp',
       'Bridge Highway Segment', 'Garage Lot Name', 'Ferry Direction',
       'Ferry Terminal Name', 'Latitude', 'Longitude', 'Location',
       'Resolution_Time', 'Day of Week', 'Day of Month', 'Month', 'Year'],
      dtype='object')
```

Major insght patterns

In [6]:
```
#Most frequent complaints
(df_perfect['Complaint Type'].value_counts()).head().plot(kind = 'bar', figsize = (10,6), title = 'Most Common Compla
```

Out[6]:
```
<AxesSubplot:title={'center':'Most Common Complaints'}>
```

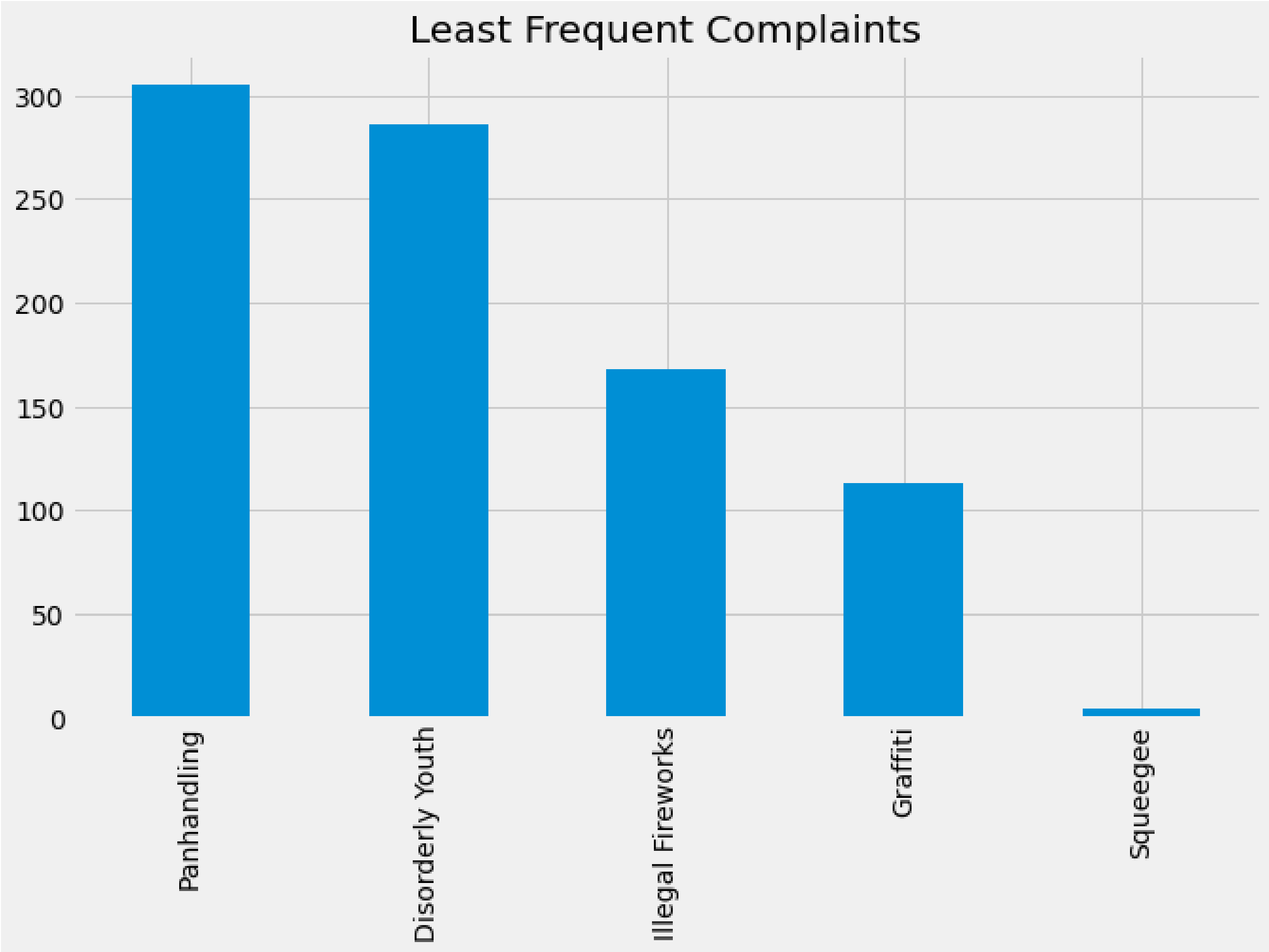


In [7]:

```
#Least frequent cmoplaints
(df_perfect['Complaint Type'].value_counts()).tail().plot(kind = 'bar', figsize = (10,6), title = 'Least Frequent Cor
```

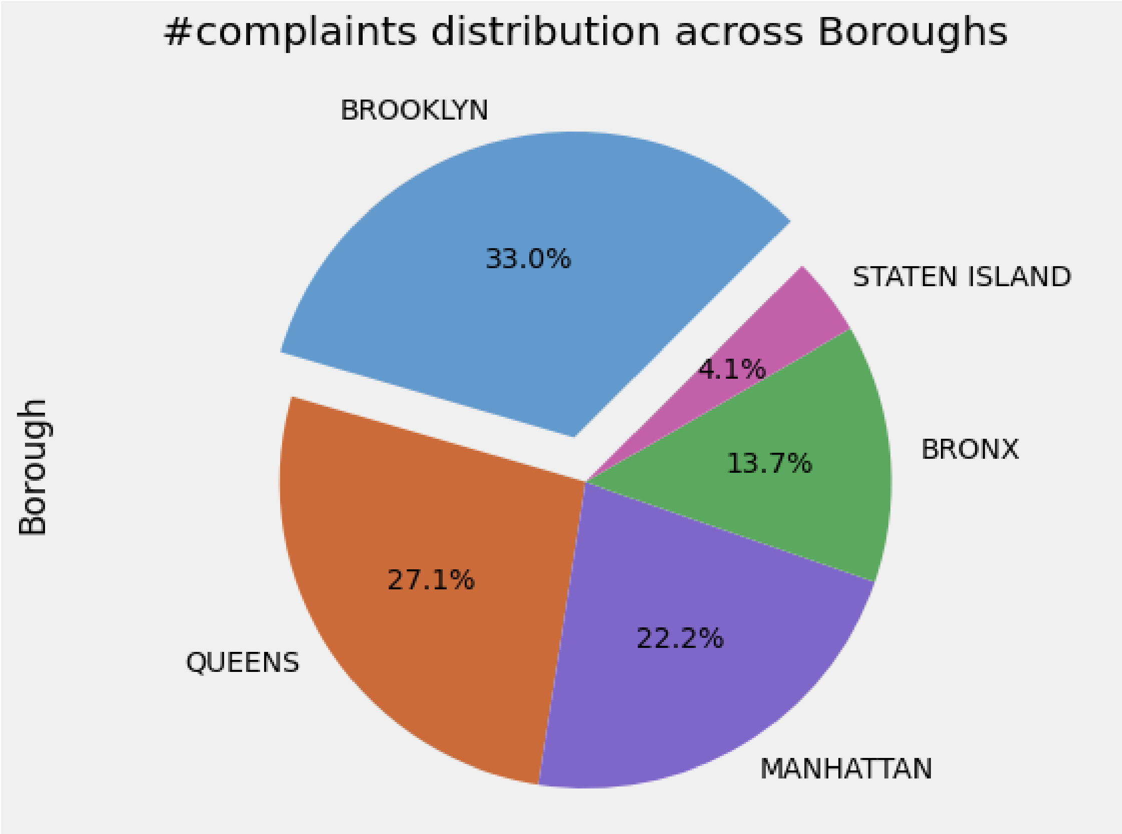
Out[7]:

```
<AxesSubplot:title={'center':'Least Frequent Complaints'}>
```



In [8]:

```
#Complaints distribution across Boroughs
colors = ['#639ace', '#ca6b39', '#7f67ca', '#5ba85f', '#c360aa', '#a7993f', '#cc566a']
df_perfect['Borough'].value_counts().plot(kind = 'pie', autopct = '%1.1f%%',
                                          explode = (0.15, 0, 0, 0, 0), startangle = 45, shadow=False, colors = colors
#plt.legend(title = 'BOROUGH', loc = 'upper right', bbox_to_anchor = (1.5,1))
plt.axis('equal')
plt.title('#complaints distribution across Boroughs\n')
plt.tight_layout()
plt.show()
```



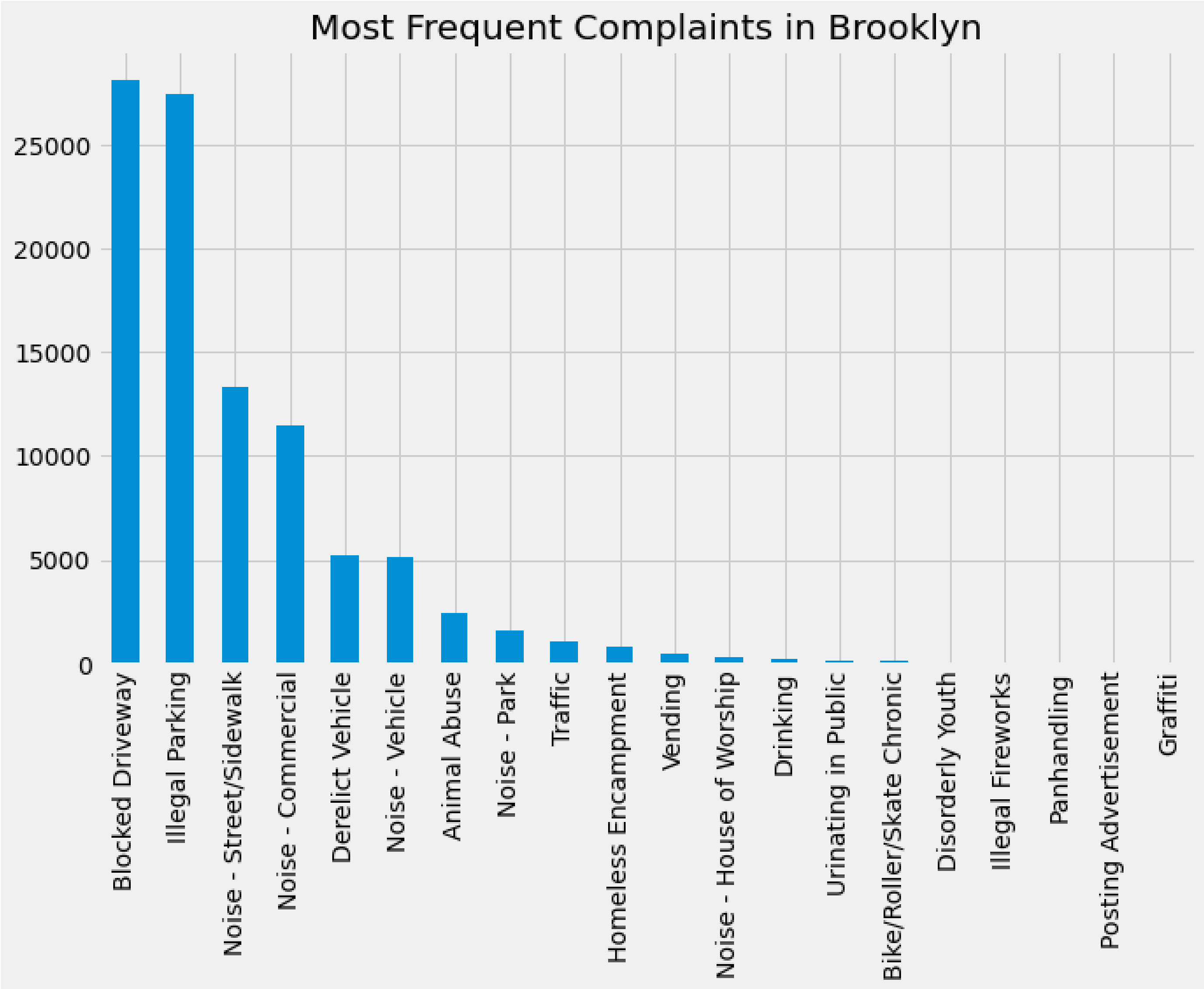
In [9]:
```
#Analysis of Brooklyn Borough which has highest number of complaints
df_Brooklyn = df_perfect[df_perfect['Borough'] == 'BROOKLYN']
```

In [10]:
```
#shape
df_Brooklyn.shape
```

Out[10]:
```
(98295, 57)
```

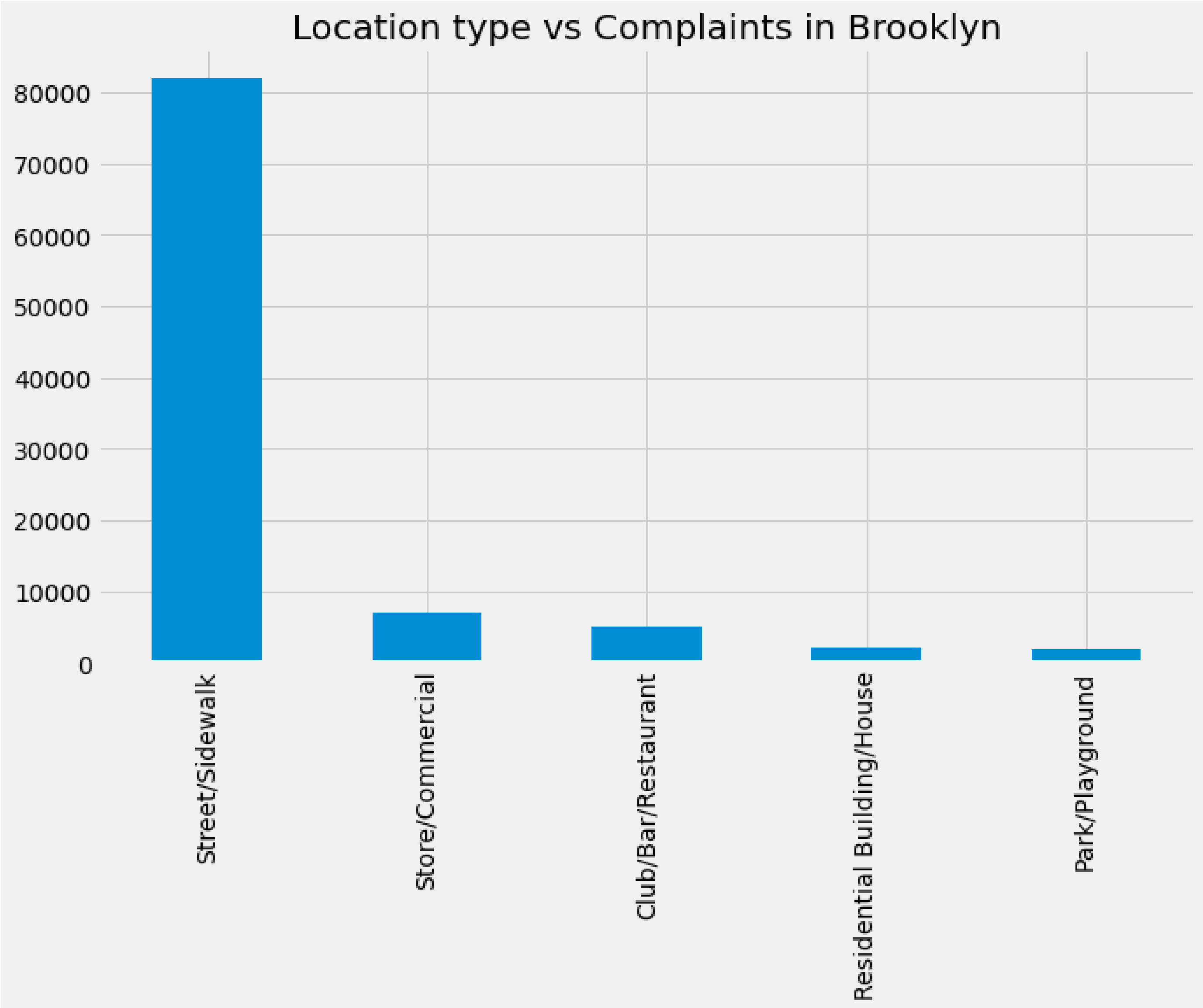
In [11]:
```
(df_Brooklyn['Complaint Type'].value_counts()).head(25).plot(kind = 'bar', figsize = (10, 6), title = 'Most Frequent
```

Out[11]:
```
<AxesSubplot:title={'center':'Most Frequent Complaints in Brooklyn'}>
```



In [12]:
```
#Location type vs complaints
(df_Brooklyn['Location Type'].value_counts()).head().plot(kind = 'bar', figsize=(10,6), title = 'Location type vs Cor
```

Out[12]: <AxesSubplot:title={'center':'Location type vs Complaints in Brooklyn'}>



In [13]:
```
#Analysis of most frequent complaint types in Brooklyn
df_perfect[df_perfect['Complaint Type'] == 'Blocked Driveway']['Descriptor'].value_counts()
```

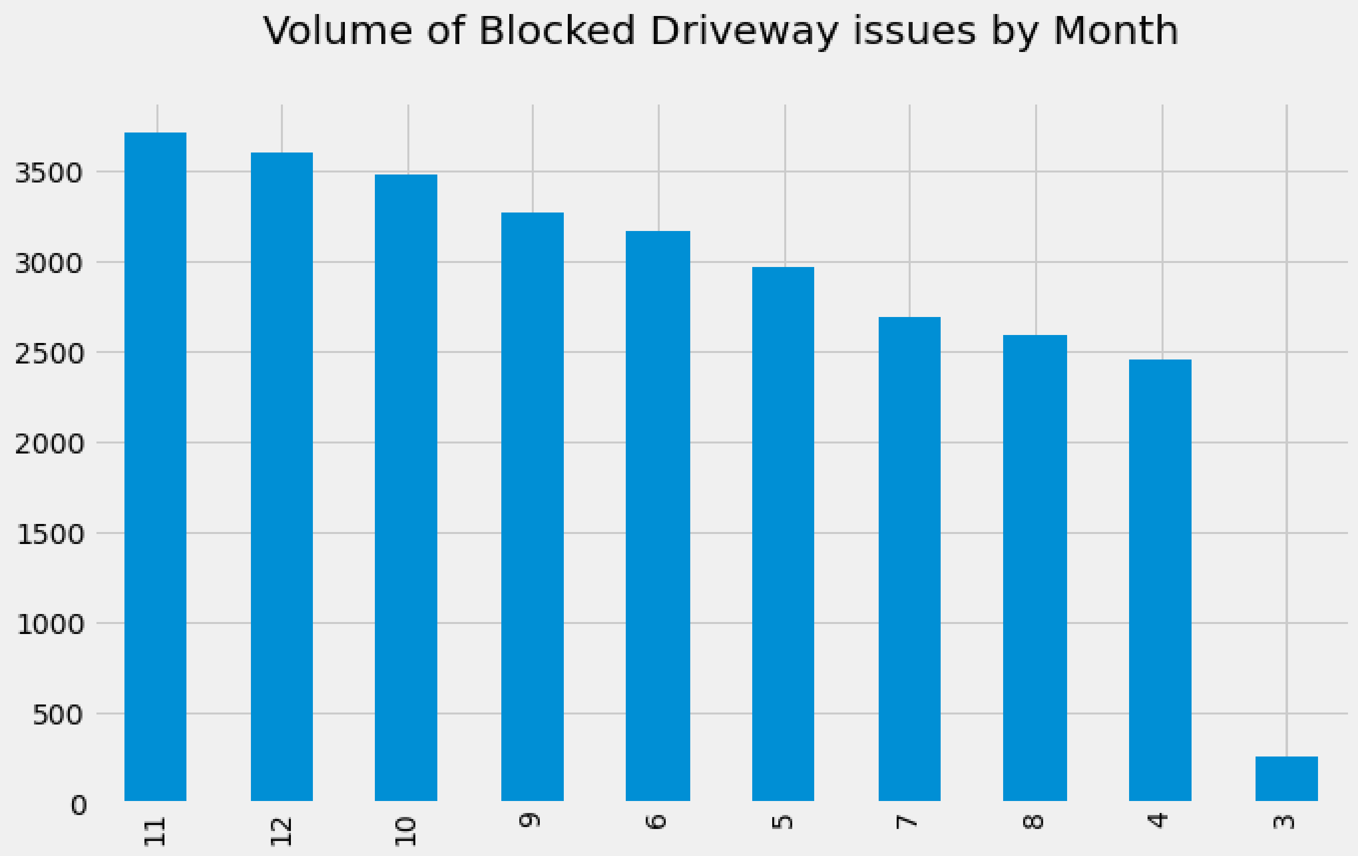
Out[13]:
```
No Access         56786
Partial Access    19967
```

Name: Descriptor, dtype: int64

In [14]:
```
df_Brook_blocked = df_Brooklyn[df_Brooklyn['Complaint Type'] == 'Blocked Driveway']
```

In [15]:
```
df_Brook_blocked['Month'].value_counts().plot(kind = 'bar', figsize = (10, 6), title = 'Volume of Blocked Driveway is
```

Out[15]: <AxesSubplot:title={'center':'Volume of Blocked Driveway issues by Month\n'}>



'Request_closing_time' in seconds, grouping them for different locations , order by complaint type

In [16]:
```
df_avg_res_time = df_perfect.groupby(['City', 'Complaint Type']).Resolution_Time.mean()
```

```
df_avg_res_time.head(25)
```

Out[16]:

```
City     Complaint Type
ARVERNE  Animal Abuse                  7753.052632
         Blocked Driveway              9093.485714
         Derelict Vehicle             10685.592593
         Disorderly Youth             12928.500000
         Drinking                       859.000000
         Graffiti                      5520.000000
         Homeless Encampment           6533.250000
         Illegal Parking               8338.913793
         Noise - Commercial            8234.000000
         Noise - House of Worship      5623.909091
         Noise - Park                  4620.000000
         Noise - Street/Sidewalk       7172.620690
         Noise - Vehicle               6695.571429
         Panhandling                   3720.000000
         Urinating in Public           2491.000000
         Vending                       1740.000000
ASTORIA  Animal Abuse                 18000.608000
         Bike/Roller/Skate Chronic     6261.533333
         Blocked Driveway             17338.024064
         Derelict Vehicle             34881.299145
         Disorderly Youth             10449.333333
         Drinking                     17000.714286
         Graffiti                     50742.250000
         Homeless Encampment          17703.312500
         Illegal Fireworks             9984.500000
Name: Resolution_Time, dtype: float64
```

Average response time across complaint types in seconds

In [17]:

```
df_avg_res_time = df_perfect.groupby('Complaint Type'). Resolution_Time.mean().sort_values(ascending = True)
df_avg_res_time.head(25)
```

Out[17]:

```
Complaint Type
Posting Advertisement        7112.891975
Illegal Fireworks            9940.101190
Noise - Commercial          11291.632884
Noise - House of Worship    11495.874058
Noise - Park                12246.158157
Noise - Street/Sidewalk     12377.738882
Traffic                     12415.252002
```

```
Disorderly Youth             12810.902098
Noise - Vehicle              12918.914430
Urinating in Public          13055.991554
Bike/Roller/Skate Chronic    13523.545024
Drinking                     13879.309748
Vending                      14449.060358
Squeegee                     14564.250000
Homeless Encampment          15716.052536
Panhandling                  15741.963934
Illegal Parking              16149.479466
Blocked Driveway             17057.298659
Animal Abuse                 18768.513712
Graffiti                     25744.504425
Derelict Vehicle             26445.913579
Name: Resolution_Time, dtype: float64
```

From the above data we can reject the null hypothesis since the average response time across complaint type are not equeal.

Null Hypothesis : Average response time across complaint type are equal. Alternate Hypothesis : Average response time across complaint type are not equal.

Following complains have resolution times which are very close : Disorderly youth 12810.902098 and Noise- Vehicle 12918.914430

One group can be formed for these complaints and one way anova for this can be performed

In [18]:
```
df_dis_youth = df_perfect[df_perfect['Complaint Type'] == 'Disorderly Youth']
df_dis_youth = df_dis_youth.loc[:,['Resolution_Time']]
df_dis_youth.head()
```

Out[18]:

	Resolution_Time
Unique Key	
32274507	713.0

	Resolution_Time
Unique Key	
32244468	4605.0
32225263	2345.0
32227341	19415.0
32191432	6849.0

In [19]:
```
df_noise_veh = df_perfect[df_perfect['Complaint Type'] == 'Noise - Vehicle']
df_noise_veh = df_noise_veh.loc[:,['Resolution_Time']]
df_noise_veh.head()
```

Out[19]:

	Resolution_Time
Unique Key	
32307159	22949.0
32308722	7254.0
32308107	11319.0
32308108	10937.0
32306622	2615.0

In [20]:
```
df_type_res = df_perfect.loc[:,['Complaint Type', 'Resolution_Time']]
df_type_res.head()
df_type_res.columns
```

Out[20]:
```
Index(['Complaint Type', 'Resolution_Time'], dtype='object')
```

In [21]:
```
#stats f_oneway functiin takes the groups as input and returs F and P value
fvalue,pvalue = stats.f_oneway(df_dis_youth, df_noise_veh)
pvalue
```

Out[21]:
```
array([0.91269878])
```

Null hypothesis to be accepted as p value close to 1

One way ANOVA for posting advertisement and Derelict vehicle

In [22]:
```
df_post_ad = df_perfect[df_perfect['Complaint Type'] == 'Posting Advertisement']
df_post_ad = df_post_ad.loc[:, ['Resolution_Time']]
df_post_ad.head()
```

Out[22]:

	Resolution_Time
Unique Key	
32306752	7596.0
32307464	7745.0
32308949	7834.0
32307323	8042.0
32306034	8137.0

In [23]:
```
df_der_veh = df_perfect[df_perfect['Complaint Type'] == 'Derelict Vehicle']
df_der_veh = df_der_veh.loc[:, ['Resolution_Time']]
df_der_veh.head()
```

Out[23]:

	Resolution_Time
Unique Key	
32309424	37763.0
32306497	14221.0
32305124	4913.0
32308002	14879.0
32305798	2712.0

In [24]:
```
fvalue, pvalue = stats.f_oneway(df_post_ad, df_der_veh)
pvalue
```

Out[24]:
```
array([7.28776953e-35])
```

Null hypothesis to be rejected as p value < 0.05

ANOVA table for complaint type and resolution time

In [25]:
```
#get anova table for complaint time and resolution type

#reshape df suitable for stats model
df_perfect['Complaint_Type'] = df_perfect['Complaint Type']
df_type_res = df_perfect.loc[:, ['Complaint_Type', 'Resolution_Time']]

#Oridnary least squares model
model = ols('Resolution_Time ~ Complaint_Type', data = df_type_res).fit()
anova_table = sm.stats.anova_lm(model, typ = 2)
anova_table
```

Out[25]:

	sum_sq	df	F	PR(>F)
Complaint_Type	3.784839e+12	20.0	410.258598	0.0
Residual	1.374816e+14	298047.0	NaN	NaN

Null Hypothesis to be rejected since pvalue < 0.05

Crosstab and chi square test for Location and Complaint type

In [26]:
```
df_city_type = pd.crosstab(df_perfect.City , df_perfect.Complaint_Type)
```

In [27]:
```
#chi square test with similar proportions
from scipy.stats import chi2_contingency
from scipy.stats import chi2
#contigency table
table = df_city_type
#print(table)
stat, p, dof, expected = chi2_contingency(table)
print('dof=%d' % dof)
print(expected)
# interpret test-statistic
```

```python
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
# interpret p-value
alpha = 1.0 - prob
print('significance=%.3f, p=%.3f' % (alpha, p))
if p <= alpha:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=1040
[[5.73350737e+00 3.11515400e-01 5.66574169e+01 ... 3.31741755e+00
  4.37007385e-01 2.80068584e+00]
 [1.64968644e+02 8.96314763e+00 1.63018841e+03 ... 9.54511504e+01
  1.25738943e+01 8.05833700e+01]
 [1.86599603e+01 1.01384103e+00 1.84394139e+02 ... 1.07966862e+01
  1.42226040e+00 9.11495938e+00]
 ...
 [6.41892211e+01 3.48755650e+00 6.34305536e+02 ... 3.71399974e+01
  4.89249632e+00 3.13549511e+01]
 [9.23615914e+01 5.01822989e+00 9.12699480e+02 ... 5.34405809e+01
  7.03979170e+00 4.51165029e+01]
 [3.12736765e+00 1.69917491e-01 3.09040456e+01 ... 1.80950048e+00
  2.38367665e-01 1.52764682e+00]]
probability=0.950, critical=1116.137, stat=110425.867
Dependent (reject H0)
significance=0.050, p=0.000
Dependent (reject H0)
```

In [ ]: