

customer-service-requests-analysis

Oct 11, 2023

1 Customer Service Requests Analysis

```
[1]: #import library
import pandas as pd
import numpy as np
import matplotlib as mpl
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use(['fivethirtyeight'])
mpl.rcParams['lines.linewidth'] = 4
import warnings
warnings.filterwarnings("ignore")
import scipy.stats as stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

1.0.1 Importing Dataset : NY 311 Service-Requests

```
[2]: #Import the data
df = pd.read_csv('311_Service_Requests_from_2010_to_Present.
↳csv',low_memory=False, header=0,
    sep=',', parse_dates=['Created Date', 'Closed Date', 'Resolution Action_
↳Updated Date'],index_col='Unique Key')
```

Converting 'Created Date' and Closed Date' to datetime datatype Removing null and junk data

```
[3]: def prepareData(df):
    df['Resolution_Time'] = (df['Closed Date'] - df['Created Date']).dt.
↳total_seconds() #####This Days divide by 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
```

```
[4]: #Looking for shape
df_perfect = prepareData(df)
df_perfect.shape
```

```
[4]: (361542, 57)
```

```
[5]: df_perfect.head()
```

```
[5]:
```

	Created Date	Closed Date	Agency	\
Unique Key				
32310363	2015-12-31 23:59:45	2016-01-01 00:55:15	NYPD	
32309934	2015-12-31 23:59:44	2016-01-01 01:26:57	NYPD	
32309159	2015-12-31 23:59:29	2016-01-01 04:51:03	NYPD	
32305098	2015-12-31 23:57:46	2016-01-01 07:43:13	NYPD	
32306529	2015-12-31 23:56:58	2016-01-01 03:24:42	NYPD	

	Agency Name	Complaint Type	\
Unique Key			
32310363	New York City Police Department	Noise - Street/Sidewalk	
32309934	New York City Police Department	Blocked Driveway	
32309159	New York City Police Department	Blocked Driveway	
32305098	New York City Police Department	Illegal Parking	
32306529	New York City Police Department	Illegal Parking	

	Descriptor	Location Type	Incident Zip	\
Unique Key				
32310363	Loud Music/Party	Street/Sidewalk	10034.0	
32309934	No Access	Street/Sidewalk	11105.0	
32309159	No Access	Street/Sidewalk	10458.0	
32305098	Commercial Overnight Parking	Street/Sidewalk	10461.0	
32306529	Blocked Sidewalk	Street/Sidewalk	11373.0	

	Incident Address	Street Name	... Ferry Direction	\
Unique Key				
32310363	71 VERMILYEA AVENUE	VERMILYEA AVENUE	...	NaN
32309934	27-07 23 AVENUE	23 AVENUE	...	NaN
32309159	2897 VALENTINE AVENUE	VALENTINE AVENUE	...	NaN
32305098	2940 BAISLEY AVENUE	BAISLEY AVENUE	...	NaN
32306529	87-14 57 ROAD	57 ROAD	...	NaN

	Ferry Terminal Name	Latitude	Longitude	\
Unique Key				
32310363	NaN	40.865682	-73.923501	
32309934	NaN	40.775945	-73.915094	

32309159	NaN	40.870325	-73.888525
32305098	NaN	40.835994	-73.828379
32306529	NaN	40.733060	-73.874170

	Location	Resolution_Time	\
Unique Key			
32310363	(40.86568153633767, -73.92350095571744)	3330.0	
32309934	(40.775945312321085, -73.91509393898605)	5233.0	
32309159	(40.870324522111424, -73.88852464418646)	17494.0	
32305098	(40.83599404683083, -73.82837939584206)	27927.0	
32306529	(40.733059618956815, -73.87416975810375)	12464.0	

	Day of Week	Day of Month	Month	Year
Unique Key				
32310363	3	31	12	2015
32309934	3	31	12	2015
32309159	3	31	12	2015
32305098	3	31	12	2015
32306529	3	31	12	2015

[5 rows x 57 columns]

```
[6]: df_perfect.tail()
```

	Created Date	Closed Date	Agency	\
Unique Key				
29609918	2015-01-01 00:04:44	2015-01-01 10:22:31	NYPD	
29608392	2015-01-01 00:04:28	2015-01-01 02:25:02	NYPD	
29607589	2015-01-01 00:01:30	2015-01-01 00:20:33	NYPD	
29610889	2015-01-01 00:01:29	2015-01-01 02:42:22	NYPD	
29611816	2015-01-01 00:00:50	2015-01-01 02:47:50	NYPD	

	Agency Name	Complaint Type	\
Unique Key			
29609918	New York City Police Department	Illegal Parking	
29608392	New York City Police Department	Noise - Vehicle	
29607589	New York City Police Department	Noise - Street/Sidewalk	
29610889	New York City Police Department	Blocked Driveway	
29611816	New York City Police Department	Blocked Driveway	

	Descriptor	Location Type	Incident Zip	\
Unique Key				
29609918	Blocked Hydrant	Street/Sidewalk	11421.0	
29608392	Car/Truck Horn	Street/Sidewalk	10468.0	
29607589	Loud Music/Party	Street/Sidewalk	10031.0	
29610889	No Access	Street/Sidewalk	10466.0	
29611816	No Access	Street/Sidewalk	11420.0	

	Incident Address	Street Name	...	Ferry Direction	\
Unique Key			...		
29609918	84-25 85 ROAD	85 ROAD	...	NaN	
29608392	2555 SEDGWICK AVENUE	SEDGWICK AVENUE	...	NaN	
29607589	508 WEST 139 STREET	WEST 139 STREET	...	NaN	
29610889	931 EAST 226 STREET	EAST 226 STREET	...	NaN	
29611816	123-19 135 STREET	135 STREET	...	NaN	

	Ferry Terminal Name	Latitude	Longitude	\
Unique Key				
29609918	NaN	40.695145	-73.860949	
29608392	NaN	40.867830	-73.907178	
29607589	NaN	40.821647	-73.950873	
29610889	NaN	40.886361	-73.853290	
29611816	NaN	40.674212	-73.803585	

	Location	Resolution_Time	\
Unique Key			
29609918	(40.69514470265117, -73.86094888534394)	37067.0	
29608392	(40.86782963689454, -73.90717786644662)	8434.0	
29607589	(40.821646626438095, -73.95087342885292)	1143.0	
29610889	(40.88636077906953, -73.85329048666742)	9653.0	
29611816	(40.674211762243935, -73.80358548685278)	10020.0	

	Day of Week	Day of Month	Month	Year
Unique Key				
29609918	3	1	1	2015
29608392	3	1	1	2015
29607589	3	1	1	2015
29610889	3	1	1	2015
29611816	3	1	1	2015

[5 rows x 57 columns]

```
[7]: df.isna().sum()
```

```
[7]: Created Date          0
      Closed Date          2381
      Agency              0
      Agency Name          0
      Complaint Type       0
      Descriptor          6501
      Location Type        133
      Incident Zip         2998
      Incident Address     51699
      Street Name          51699
```

Cross Street 1	57188
Cross Street 2	57805
Intersection Street 1	313438
Intersection Street 2	314046
Address Type	3252
City	2997
Landmark	364183
Facility Type	2389
Status	0
Due Date	3
Resolution Description	0
Resolution Action Updated Date	2402
Community Board	0
Borough	0
X Coordinate (State Plane)	4030
Y Coordinate (State Plane)	4030
Park Facility Name	0
Park Borough	0
School Name	0
School Number	0
School Region	1
School Code	1
School Phone Number	0
School Address	0
School City	0
School State	0
School Zip	1
School Not Found	0
School or Citywide Complaint	364558
Vehicle Type	364558
Taxi Company Borough	364558
Taxi Pick Up Location	364558
Bridge Highway Name	364261
Bridge Highway Direction	364261
Road Ramp	364296
Bridge Highway Segment	364296
Garage Lot Name	364558
Ferry Direction	364557
Ferry Terminal Name	364556
Latitude	4030
Longitude	4030
Location	4030
Resolution_Time	2381

dtype: int64

```
[8]: df_perfect.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
Int64Index: 361542 entries, 32310363 to 29611816
```

```
Data columns (total 57 columns):
```

#	Column	Non-Null Count	Dtype
0	Created Date	361542 non-null	datetime64[ns]
1	Closed Date	361542 non-null	datetime64[ns]
2	Agency	361542 non-null	object
3	Agency Name	361542 non-null	object
4	Complaint Type	361542 non-null	object
5	Descriptor	355049 non-null	object
6	Location Type	361420 non-null	object
7	Incident Zip	361501 non-null	float64
8	Incident Address	309865 non-null	object
9	Street Name	309865 non-null	object
10	Cross Street 1	306722 non-null	object
11	Cross Street 2	306713 non-null	object
12	Intersection Street 1	50504 non-null	object
13	Intersection Street 2	50504 non-null	object
14	Address Type	361247 non-null	object
15	City	361501 non-null	object
16	Landmark	375 non-null	object
17	Facility Type	361533 non-null	object
18	Status	361542 non-null	object
19	Due Date	361541 non-null	object
20	Resolution Description	361542 non-null	object
21	Resolution Action Updated Date	361503 non-null	datetime64[ns]
22	Community Board	361542 non-null	object
23	Borough	361542 non-null	object
24	X Coordinate (State Plane)	360469 non-null	float64
25	Y Coordinate (State Plane)	360469 non-null	float64
26	Park Facility Name	361542 non-null	object
27	Park Borough	361542 non-null	object
28	School Name	361542 non-null	object
29	School Number	361542 non-null	object
30	School Region	361542 non-null	object
31	School Code	361542 non-null	object
32	School Phone Number	361542 non-null	object
33	School Address	361542 non-null	object
34	School City	361542 non-null	object
35	School State	361542 non-null	object
36	School Zip	361542 non-null	object
37	School Not Found	361542 non-null	object
38	School or Citywide Complaint	0 non-null	float64
39	Vehicle Type	0 non-null	float64
40	Taxi Company Borough	0 non-null	float64
41	Taxi Pick Up Location	0 non-null	float64
42	Bridge Highway Name	297 non-null	object

```

43 Bridge Highway Direction      297 non-null    object
44 Road Ramp                    262 non-null    object
45 Bridge Highway Segment       262 non-null    object
46 Garage Lot Name              0 non-null      float64
47 Ferry Direction              0 non-null      object
48 Ferry Terminal Name          0 non-null      object
49 Latitude                     360469 non-null float64
50 Longitude                    360469 non-null float64
51 Location                     360469 non-null object
52 Resolution_Time              361542 non-null float64
53 Day of Week                  361542 non-null int64
54 Day of Month                 361542 non-null int64
55 Month                       361542 non-null int64
56 Year                        361542 non-null int64
dtypes: datetime64[ns](3), float64(11), int64(4), object(39)
memory usage: 160.0+ MB

```

Investigating on Insights and Patterns

```

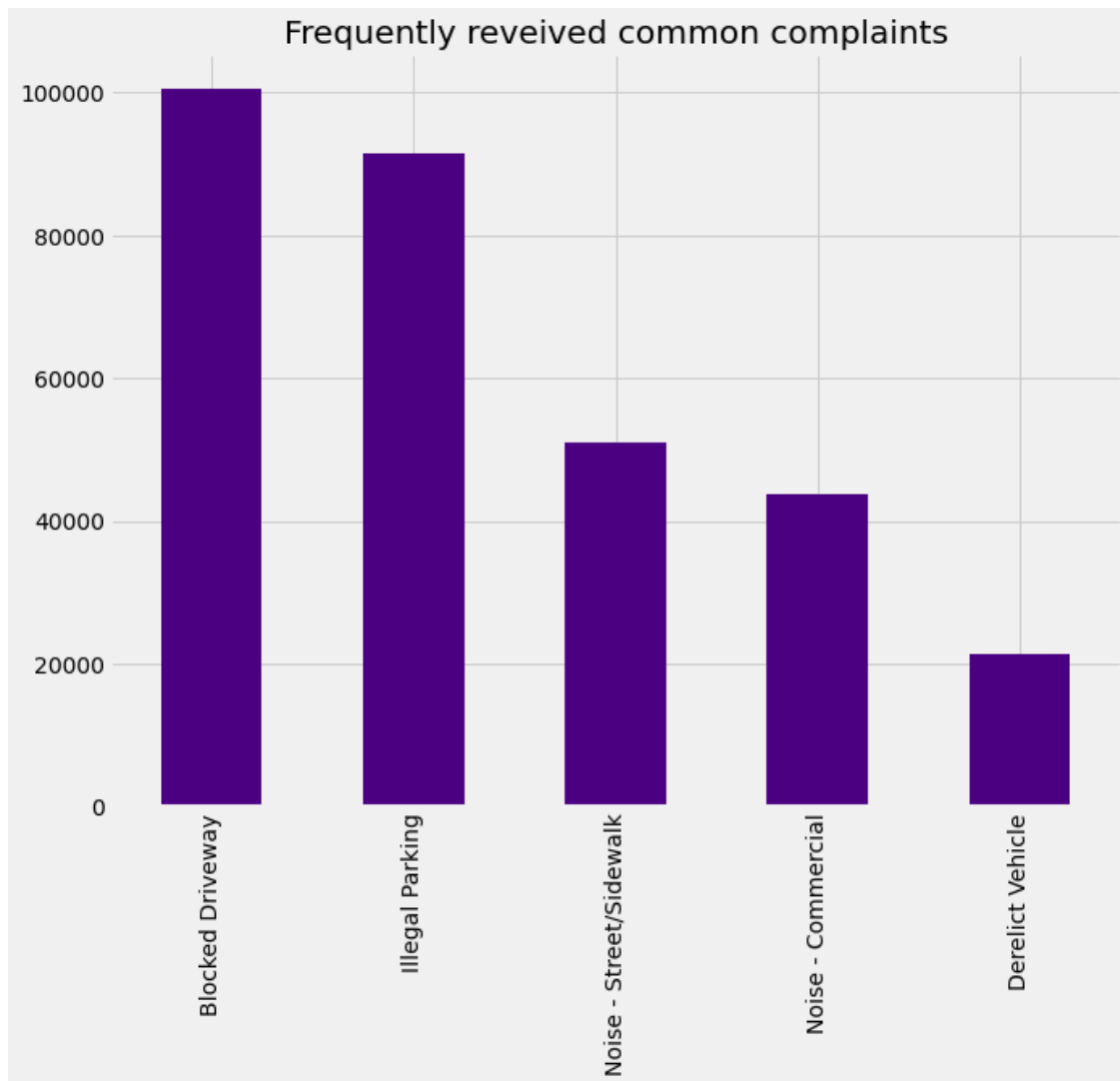
[9]: (df_perfect['Complaint Type'].value_counts()).head().plot(kind='bar',
      figsize=(10,8),color='indigo', title = 'Frequently reveived_
      ↳common complaints')

```

```

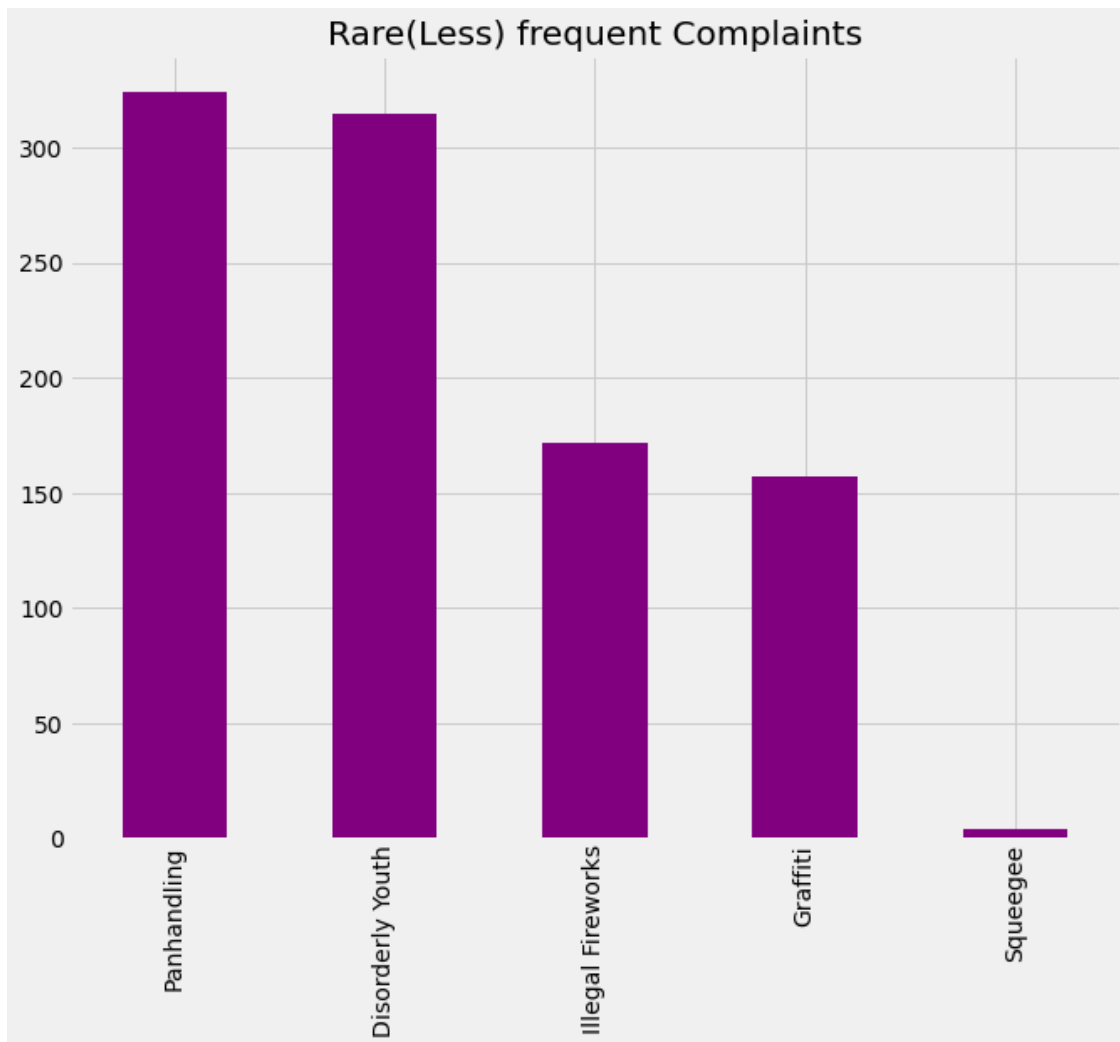
[9]: <AxesSubplot:title={'center':'Frequently reveived common complaints'}>

```

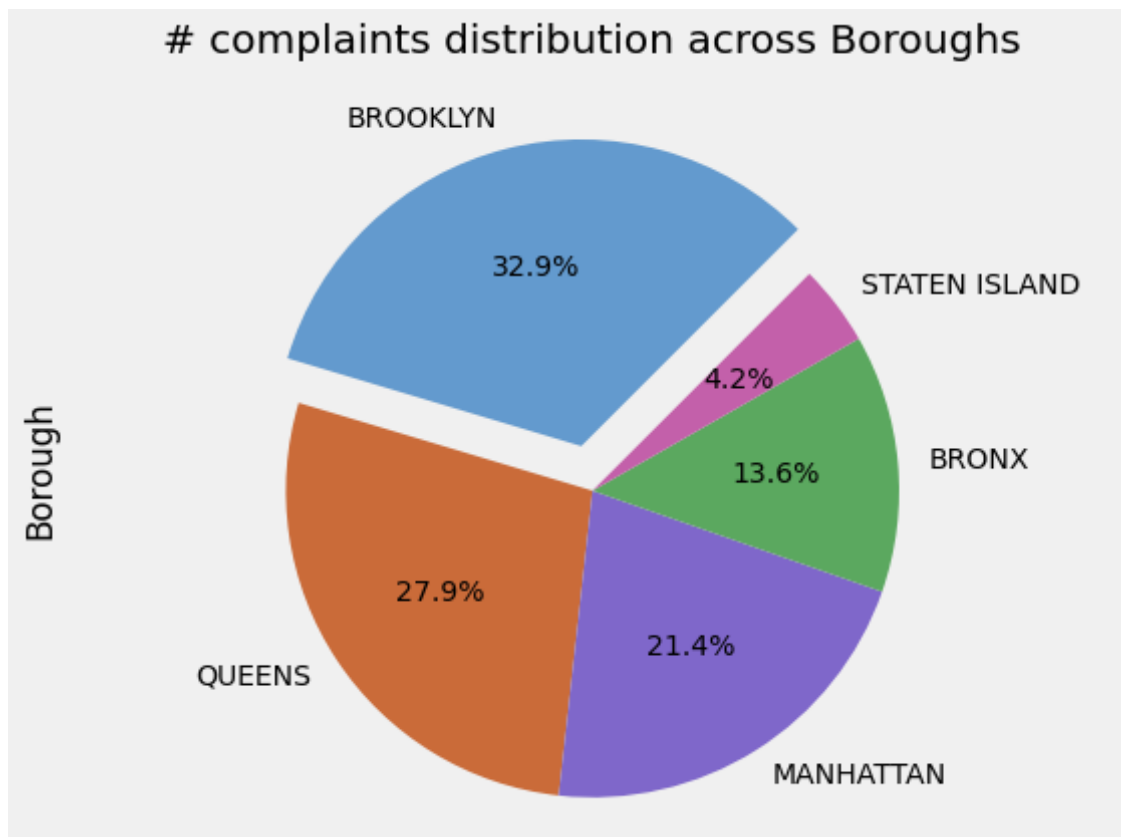


```
[10]: #Rare(Less) frequent Complaints
(df_perfect['Complaint Type'].value_counts()).tail().plot(kind='bar',
    figsize=(10,8),color='purple', title = 'Rare(Less) frequent_
    Complaints')
```

```
[10]: <AxesSubplot:title={'center':'Rare(Less) frequent Complaints'}>
```

```
[11]: # Distribution of complaints 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,
                                           figsize = (8,6))
#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()
```



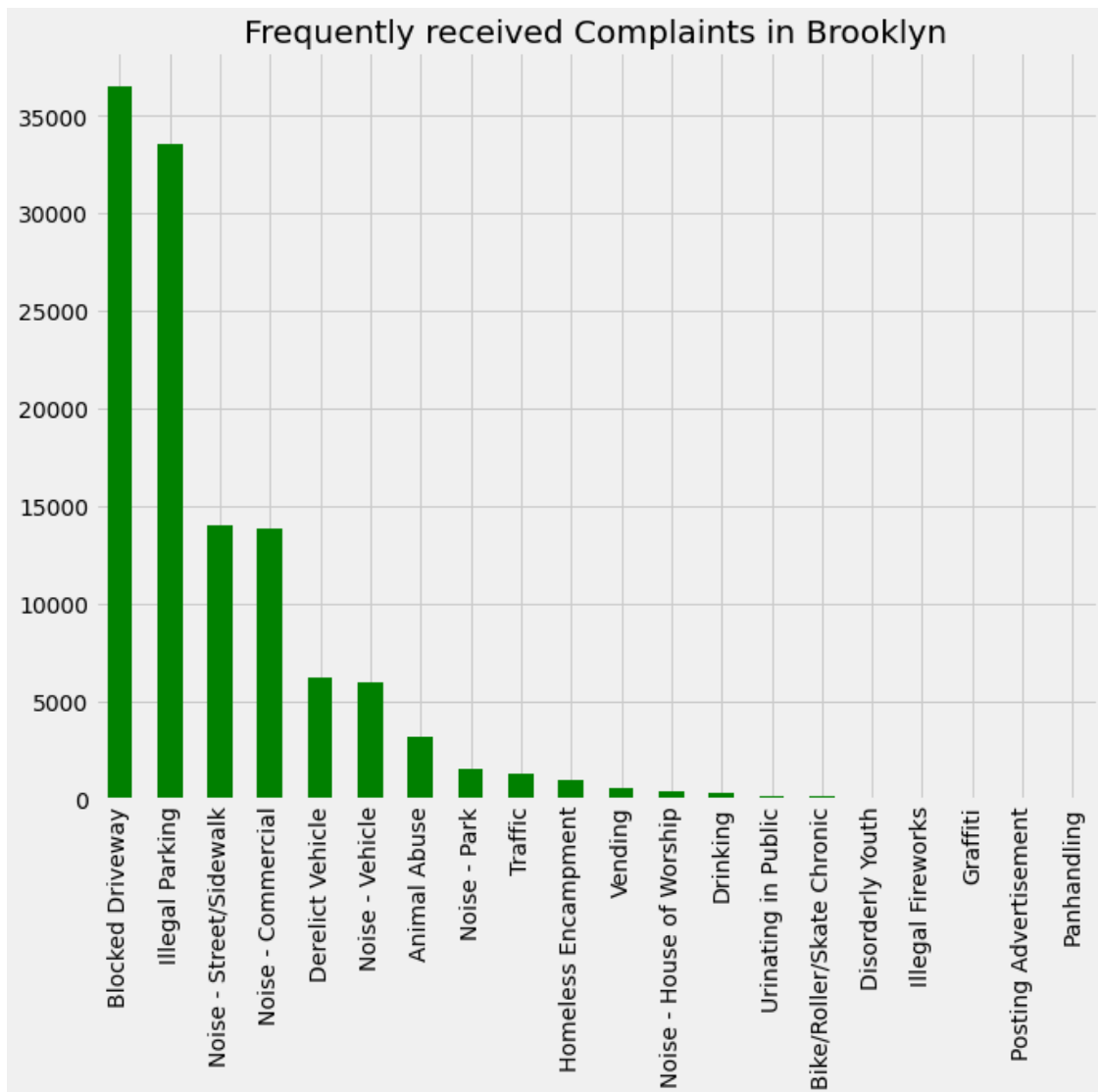
```
[12]: #Analysis for Brooklyn borough which has highest number of complains
df_Brooklyn = df_perfect[df_perfect['Borough']=='BROOKLYN']
```

```
[13]: df_Brooklyn.shape
```

```
[13]: (118851, 57)
```

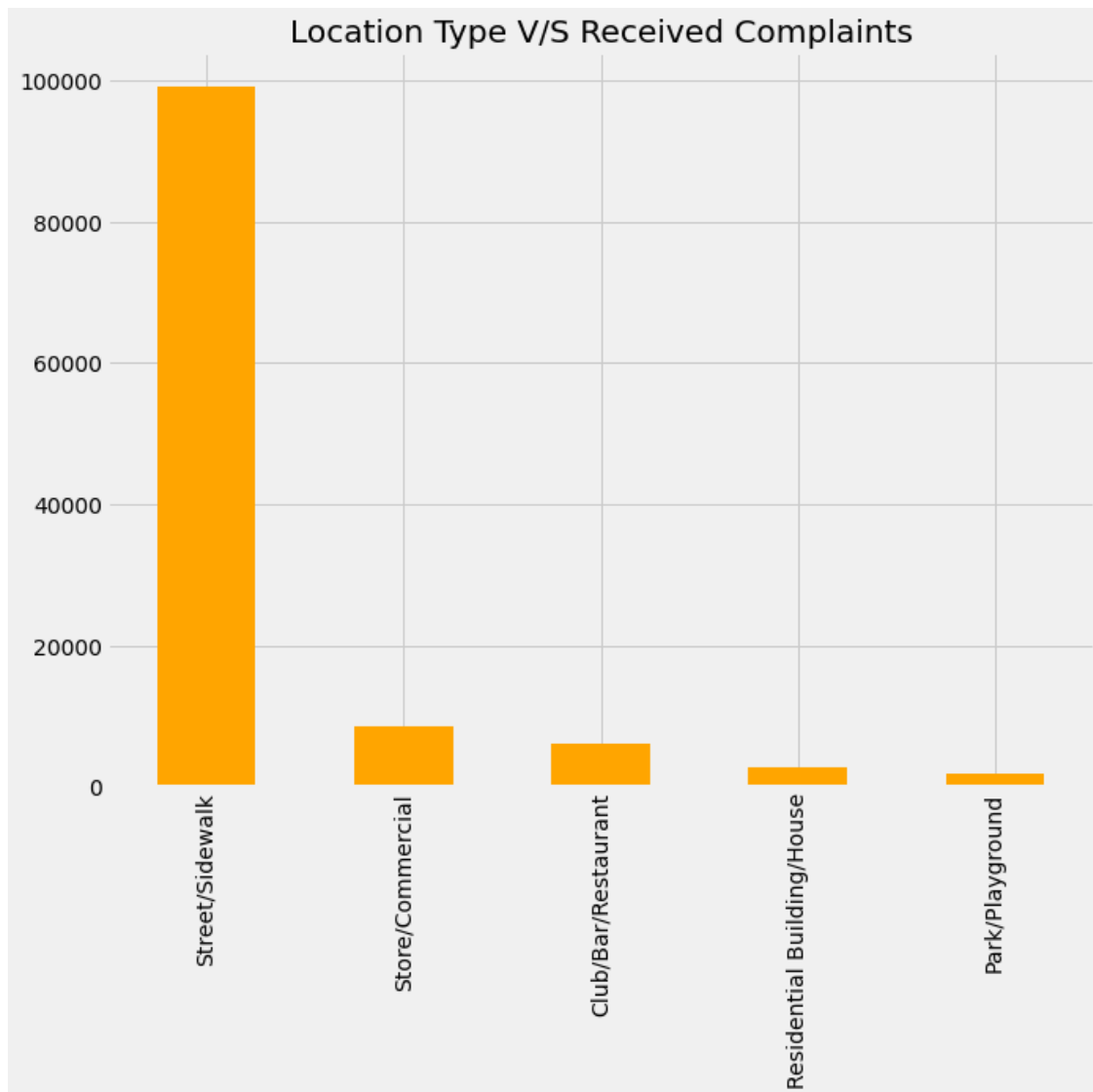
```
[14]: (df_Brooklyn['Complaint Type'].value_counts()).head(25).
      ↪ plot(kind='bar',color='green',
            figsize=(10,8),title = '
      ↪ 'Frequently received Complaints in Brooklyn')
```

```
[14]: <AxesSubplot:title={'center':'Frequently received Complaints in Brooklyn'}>
```



```
[15]: #Plotting graph : location type vs complaints received
(df_Brooklyn['Location Type'].value_counts()).head().plot(kind='bar',
↳ figsize=(10,8),color='Orange',title = 'Location Type V/S Received
↳ Complaints')
```

```
[15]: <AxesSubplot:title={'center':'Location Type V/S Received Complaints'}>
```



```
[16]: #Analyzing the Most Frequent complaint in Brooklyn
df_perfect[df_perfect['Complaint Type'] == 'Blocked Driveway']['Descriptor'].
      value_counts()
```

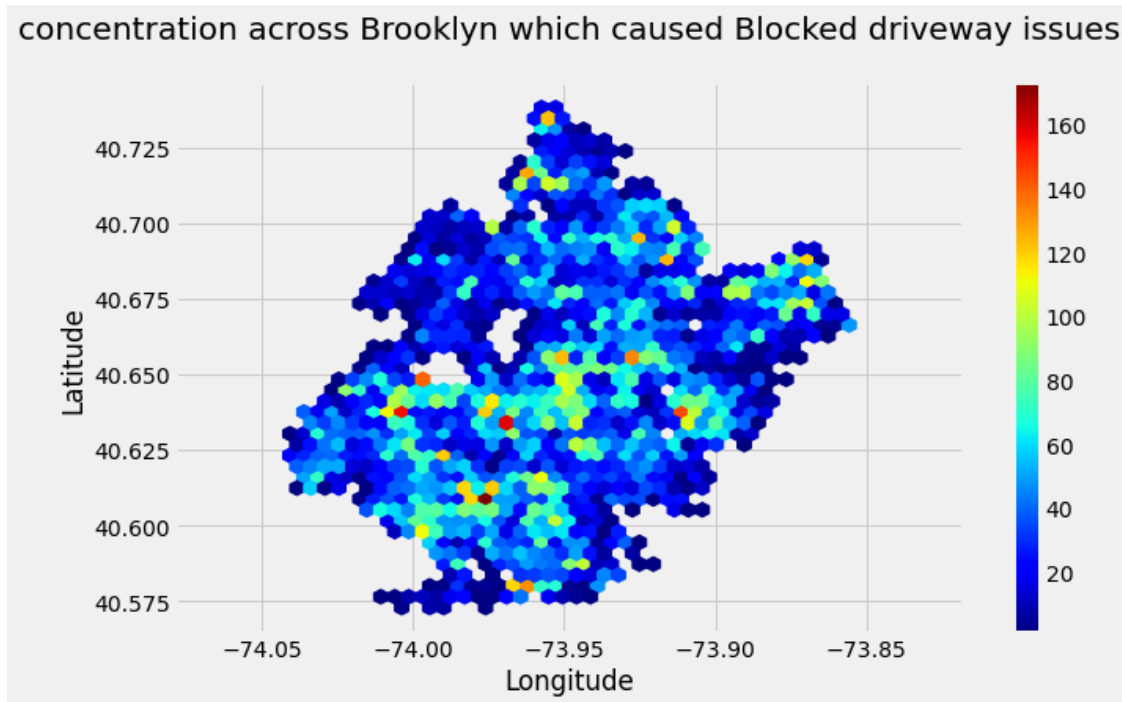
```
[16]: No Access          75657
      Partial Access    24882
      Name: Descriptor, dtype: int64
```

```
[17]: df_Brook_blocked = df_Brooklyn[df_Brooklyn['Complaint Type'] == 'Blocked_
      Driveway']
```

```
[18]: df_Brook_blocked.plot()
```

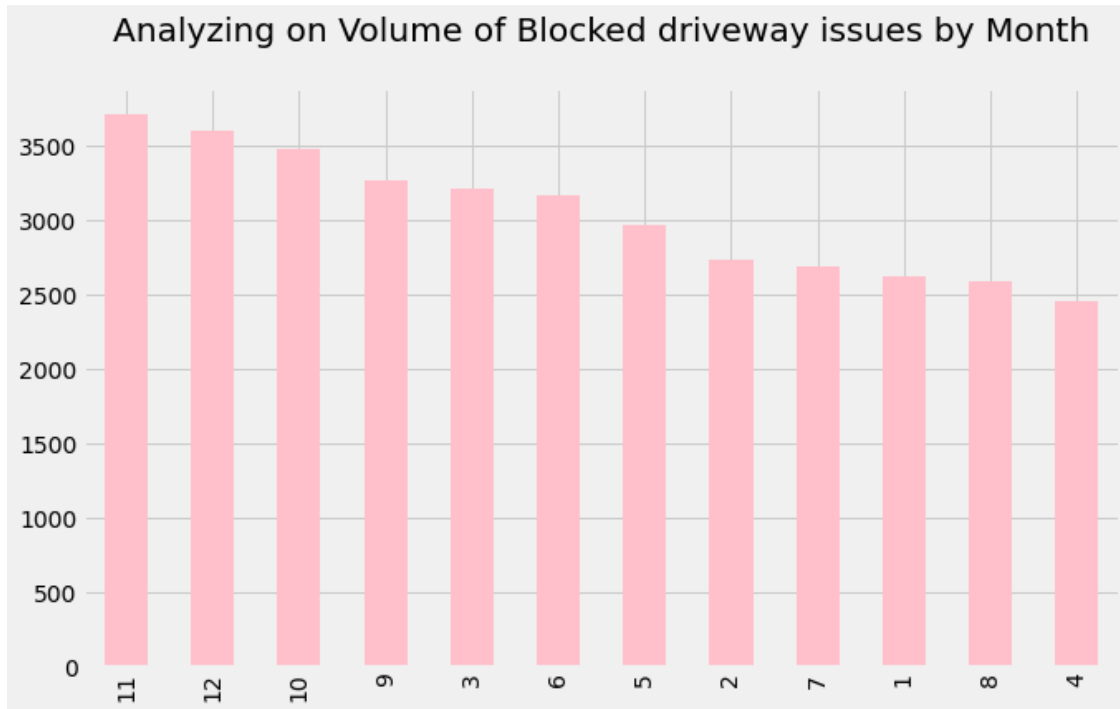
```
kind='hexbin', x='Longitude', y='Latitude', gridsize=40,title =  
↪ 'concentration across Brooklyn which caused Blocked driveway issues\n',  
colormap='jet', mincnt=1, figsize=(10,6)).axis('equal')
```

[18]: (-74.04994269716303, -73.84653003063751, 40.56459183795005, 40.746496092182724)



```
[19]: df_Brook_blocked['Month'].value_counts().plot(kind =  
↪ 'bar',color='pink',figsize=(10,6), title = 'Analyzing on Volume of Blocked_  
↪ driveway issues by Month\n')
```

[19]: <AxesSubplot:title={'center': 'Analyzing on Volume of Blocked driveway issues by Month\n'}>



1.0.2 'Request_Closing_Time' in Seconds by grouping them for different location and order by complaint type

```
[20]: df_avg_res_time_city = df_perfect.groupby(['City', 'Complaint Type']).
      ↪Resolution_Time.mean()
      #df_perfect.sort_values('Complaint Type').groupby('City')
      #
      df_avg_res_time_city.head(25)
```

```
[20]: City      Complaint Type
ARVERNE  Animal Abuse      8399.195652
         Blocked Driveway    8318.840000
         Derelict Vehicle    11394.000000
         Disorderly Youth    12928.500000
         Drinking            859.000000
         Graffiti           5508.000000
         Homeless Encampment  6541.250000
         Illegal Parking      8406.080645
         Noise - Commercial   8234.000000
         Noise - House of Worship 6653.428571
         Noise - Park         4638.000000
         Noise - Street/Sidewalk 7173.206897
         Noise - Vehicle      5673.600000
         Panhandling          3673.000000
```

	Traffic	4014.000000
	Urinating in Public	2491.000000
	Vending	1735.000000
ASTORIA	Animal Abuse	17206.882353
	Bike/Roller/Skate Chronic	6718.750000
	Blocked Driveway	16515.934517
	Derelect Vehicle	32446.598592
	Disorderly Youth	9713.800000
	Drinking	15518.279070
	Graffiti	50742.250000
	Homeless Encampment	17704.312500

Name: Resolution_Time, dtype: float64

1.0.3 Average response time(in seconds) across complaint types

```
[21]: df_avg_res_time = df_perfect.groupby('Complaint Type').Resolution_Time.mean().
      ↪sort_values(ascending=True)
      df_avg_res_time.head(21)
```

```
[21]: Complaint Type
Posting Advertisement      7286.256259
Illegal Fireworks         10113.482558
Noise - Commercial        11040.936795
Noise - House of Worship  11391.087079
Noise - Park              12194.009799
Noise - Street/Sidewalk   12206.102697
Traffic                   12309.120092
Disorderly Youth          12363.749206
Noise - Vehicle           12557.269801
Urinating in Public       12959.293292
Bike/Roller/Skate Chronic  13089.997886
Drinking                  13800.002855
Vending                   14365.309034
Squeegee                  14560.250000
Homeless Encampment       15451.384505
Illegal Parking           15590.340164
Panhandling               15765.632716
Blocked Driveway          16218.697660
Animal Abuse              18033.102859
Graffiti                 23276.343949
Derelect Vehicle          25279.866465
Name: Resolution_Time, dtype: float64
```

From the above data rejecting null hypothesis, since the average response time across complaint type are not equal. Null Hypothesis (Average response time across complaint type are equal). Alternate Hypothesis (Average response time across complaint

type are equal)

Following complains have resolution times which are very close. Disorderly Youth 12810.902098 Noise - Vehicle 12918.914430 One group can be formed for these complaints and one way Anova for this can be performed

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

```
[22]:
```

	Resolution_Time
Unique Key	
32274507	713.0
32244468	4605.0
32225263	2345.0
32227341	19415.0
32191432	6849.0

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

```
[23]:
```

	Resolution_Time
Unique Key	
32307159	22994.0
32308722	7254.0
32308107	11319.0
32308108	10937.0
32306622	2615.0

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

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

```
[25]: fvalue, pvalue = stats.f_oneway(df_dis_youth, df_noise_veh)
pvalue
```

```
[25]: array([0.83131389])
```

1.0.4 One Way Anova for Posting Advertisement and Derelict Vehicle

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



```
[26]:
```

	Resolution_Time
Unique Key	
32306752	7643.0
32307464	7798.0
32308949	7893.0
32307323	8047.0
32306034	8144.0

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

```
[27]:
```

	Resolution_Time
Unique Key	
32309424	37785.0
32306497	14224.0
32305124	4913.0
32308002	14879.0
32305798	2712.0

```
[28]: # stats f_oneway functions takes the groups as input and returns F and P-value
fvalue, pvalue = stats.f_oneway(df_post_ad, df_der_veh)
pvalue
```

```
[28]: array([1.52053985e-35])
```

Anova table for complain type and resolution time

```
[30]: df_perfect['Complaint_Type']=df_perfect['Complaint Type']
df_type_res = df_perfect.loc[:, ['Complaint_Type', 'Resolution_Time']]
# #Complaint Type
# Ordinary Least Squares (OLS) model
model = ols('Resolution_Time ~ Complaint_Type', data=df_type_res).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
anova_table
```

```
[30]:
```

	sum_sq	df	F	PR(>F)
Complaint_Type	3.892068e+12	20.0	454.111878	0.0
Residual	1.549249e+14	361521.0	NaN	NaN

Crosstab and Chi Square test for Location and Complaint type

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

```
[32]: # chi-squared test with similar proportions
from scipy.stats import chi2_contingency
from scipy.stats import chi2
# contingency table
```

```

table = df_city_type
#print(table)
stat, p, dof, expected = chi2_contingency(table)
print('dof=%d' % dof)
print(expected)
# interpret test-statistic
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
[[7.54357803e+00 3.38884263e-01 7.20311756e+01 ... 3.72127878e+00
 4.59249075e-01 2.99765699e+00]
 [2.32744139e+02 1.04556917e+01 2.22239816e+03 ... 1.14813663e+02
 1.41693412e+01 9.24875561e+01]
 [2.63588344e+01 1.18413227e+00 2.51691946e+02 ... 1.30029239e+01
 1.60471202e+00 1.04744385e+01]
 ...
 [9.03481816e+01 4.05876056e+00 8.62705431e+02 ... 4.45691381e+01
 5.50034993e+00 3.59024401e+01]
 [1.26901040e+02 5.70084453e+00 1.21173680e+03 ... 6.26008171e+01
 7.72566881e+00 5.04277665e+01]
 [4.83488012e+00 2.17199952e-01 4.61666994e+01 ... 2.38506671e+00
 2.94344967e-01 1.92127823e+00]]
probability=0.950, critical=1116.137, stat=131573.935
Dependent (reject H0)
significance=0.050, p=0.000
Dependent (reject H0)

```

[]: