CustomerServiceNYC311

September 3, 2022

0.0.1 Importing the Library

[2]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
sns.set()

import warnings
warnings.filterwarnings("ignore")

from scipy import stats
from scipy.stats import chi2_contingency

import statsmodels.api as sm
from statsmodels.formula.api import ols
```

0.0.2 Loading the Data

[3]:
```
df=pd.read_csv("311_Service_Requests_from_2010_to_Present.csv")
df.head()
```

[3]:
```
   Unique Key            Created Date            Closed Date Agency  \
0    32310363  12/31/2015 11:59:45 PM  01/01/2016 12:55:15 AM   NYPD
1    32309934  12/31/2015 11:59:44 PM  01/01/2016 01:26:57 AM   NYPD
2    32309159  12/31/2015 11:59:29 PM  01/01/2016 04:51:03 AM   NYPD
3    32305098  12/31/2015 11:57:46 PM  01/01/2016 07:43:13 AM   NYPD
4    32306529  12/31/2015 11:56:58 PM  01/01/2016 03:24:42 AM   NYPD

                       Agency Name           Complaint Type  \
0  New York City Police Department  Noise - Street/Sidewalk
1  New York City Police Department         Blocked Driveway
2  New York City Police Department         Blocked Driveway
3  New York City Police Department           Illegal Parking
4  New York City Police Department           Illegal Parking

                    Descriptor    Location Type  Incident Zip  \
```

```
0             Loud Music/Party  Street/Sidewalk       10034.0
1                    No Access  Street/Sidewalk       11105.0
2                    No Access  Street/Sidewalk       10458.0
3  Commercial Overnight Parking  Street/Sidewalk       10461.0
4             Blocked Sidewalk  Street/Sidewalk       11373.0

        Incident Address  … Bridge Highway Name Bridge Highway Direction  \
0     71 VERMILYEA AVENUE  …                 NaN                      NaN
1         27-07 23 AVENUE  …                 NaN                      NaN
2   2897 VALENTINE AVENUE  …                 NaN                      NaN
3     2940 BAISLEY AVENUE  …                 NaN                      NaN
4           87-14 57 ROAD  …                 NaN                      NaN

  Road Ramp Bridge Highway Segment Garage Lot Name Ferry Direction  \
0       NaN                    NaN             NaN             NaN
1       NaN                    NaN             NaN             NaN
2       NaN                    NaN             NaN             NaN
3       NaN                    NaN             NaN             NaN
4       NaN                    NaN             NaN             NaN

  Ferry Terminal Name   Latitude  Longitude  \
0                 NaN  40.865682 -73.923501
1                 NaN  40.775945 -73.915094
2                 NaN  40.870325 -73.888525
3                 NaN  40.835994 -73.828379
4                 NaN  40.733060 -73.874170

                                 Location
0   (40.86568153633767, -73.92350095571744)
1  (40.775945312321085, -73.91509393898605)
2  (40.870324522111424, -73.88852464418646)
3   (40.83599404683083, -73.82837939584206)
4  (40.733059618956815, -73.87416975810375)

[5 rows x 53 columns]
```

0.0.3 Descriptive Analysis

[4]:
```
df.describe()
```

[4]:
```
         Unique Key   Incident Zip  X Coordinate (State Plane)  \
count  3.645580e+05  361560.000000                3.605280e+05
mean   3.106595e+07   10858.496659                1.005043e+06
std    7.331531e+05     578.263114                2.196362e+04
min    2.960737e+07      83.000000                9.133570e+05
25%    3.049938e+07   10314.000000                9.919460e+05
50%    3.108795e+07   11209.000000                1.003470e+06
```

```
75%    3.167433e+07   11238.000000                1.019134e+06
max    3.231065e+07   11697.000000                1.067186e+06

       Y Coordinate (State Plane)  School or Citywide Complaint  Vehicle Type  \
count               360528.000000                           0.0           0.0
mean                203425.305782                           NaN           NaN
std                  29842.192857                           NaN           NaN
min                 121185.000000                           NaN           NaN
25%                 182945.000000                           NaN           NaN
50%                 201023.000000                           NaN           NaN
75%                 222790.000000                           NaN           NaN
max                 271876.000000                           NaN           NaN

       Taxi Company Borough  Taxi Pick Up Location  Garage Lot Name  \
count                   0.0                    0.0              0.0
mean                    NaN                    NaN              NaN
std                     NaN                    NaN              NaN
min                     NaN                    NaN              NaN
25%                     NaN                    NaN              NaN
50%                     NaN                    NaN              NaN
75%                     NaN                    NaN              NaN
max                     NaN                    NaN              NaN

            Latitude      Longitude
count  360528.000000  360528.000000
mean       40.724980     -73.924946
std         0.081907       0.079213
min        40.499040     -74.254937
25%        40.668742     -73.972253
50%        40.718406     -73.930643
75%        40.778166     -73.874098
max        40.912869     -73.700715
```

[5]:
```python
df.shape
```

[5]:
```
(364558, 53)
```

We see lots of missing value. All the values given in the above does not provides us very clear insights about our data so we can move ahead with Exploratory Data Analysis.

0.0.4 Feature Creation

[6]:
```python
# Converting the data into datetime format
df["Created Date"]=pd.to_datetime(df["Created Date"])
df["Closed Date"]=pd.to_datetime(df["Closed Date"])
```

[7]:
```python
#Creating the new column that consist the amount of time taken to resolve the␣
↪complaint
```

```
df["Request_Closing_Time"]=(df["Closed Date"]-df["Created Date"])

Request_Closing_Time=[]
for x in (df["Closed Date"]-df["Created Date"]):
    close=x.total_seconds()/60
    Request_Closing_Time.append(close)

df["Request_Closing_Time"]=Request_Closing_Time
```

0.0.5 Exploratory Data Analysis

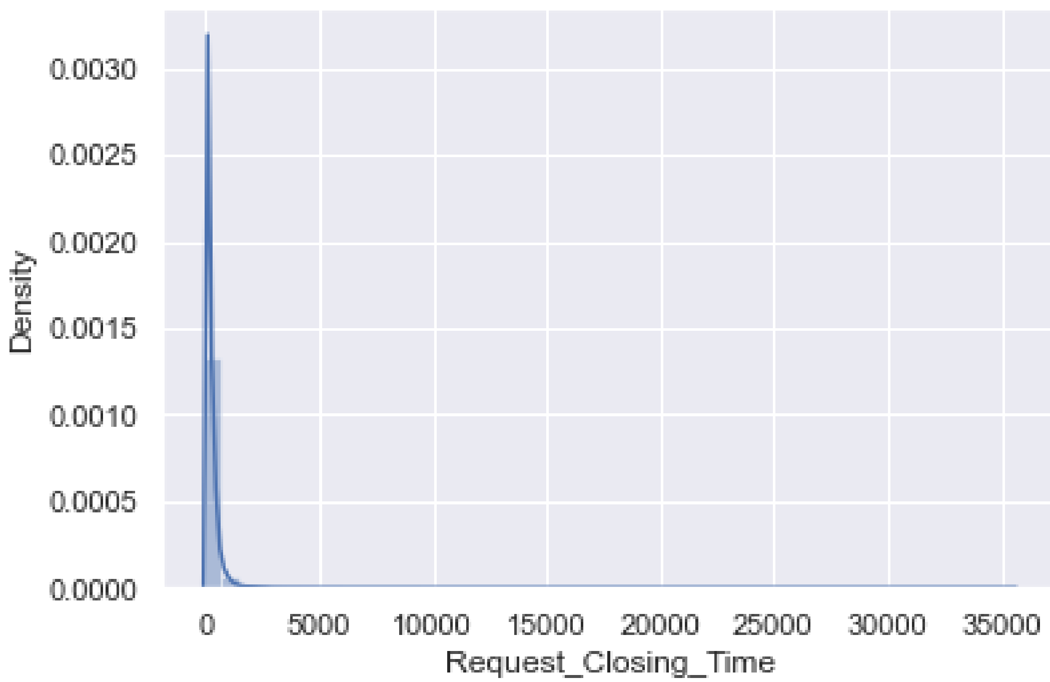
[8]:
```
df["Agency"].unique()
```

[8]:
```
array(['NYPD'], dtype=object)
```

All of our data belongs to a single agency NYPD i.e New York City Police Department.

[9]:
```
#Univariate Distribution Plot for Request Closing Time
sns.distplot(df["Request_Closing_Time"])
plt.show
```

[9]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



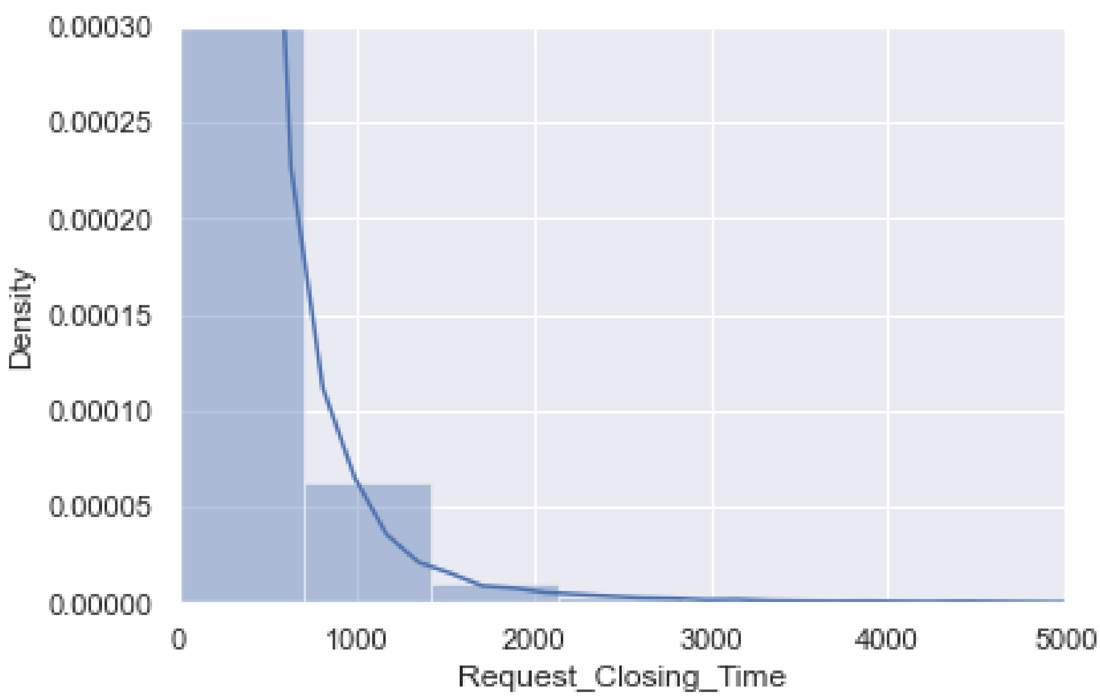
[10]:
```
print("Total Number of Concerns : ",len(df),"\n")
```

```
print("Percentage of Requests took less than 100 hour to get solved   :␣
↪",round((len(df)-(df["Request_Closing_Time"]>100).sum())/len(df)*100,2),"%")
print("Percentage of Requests took less than 1000 hour to get solved :␣
↪",round((len(df)-(df["Request_Closing_Time"]>1000).sum())/len(df)*100,2),"%")
```

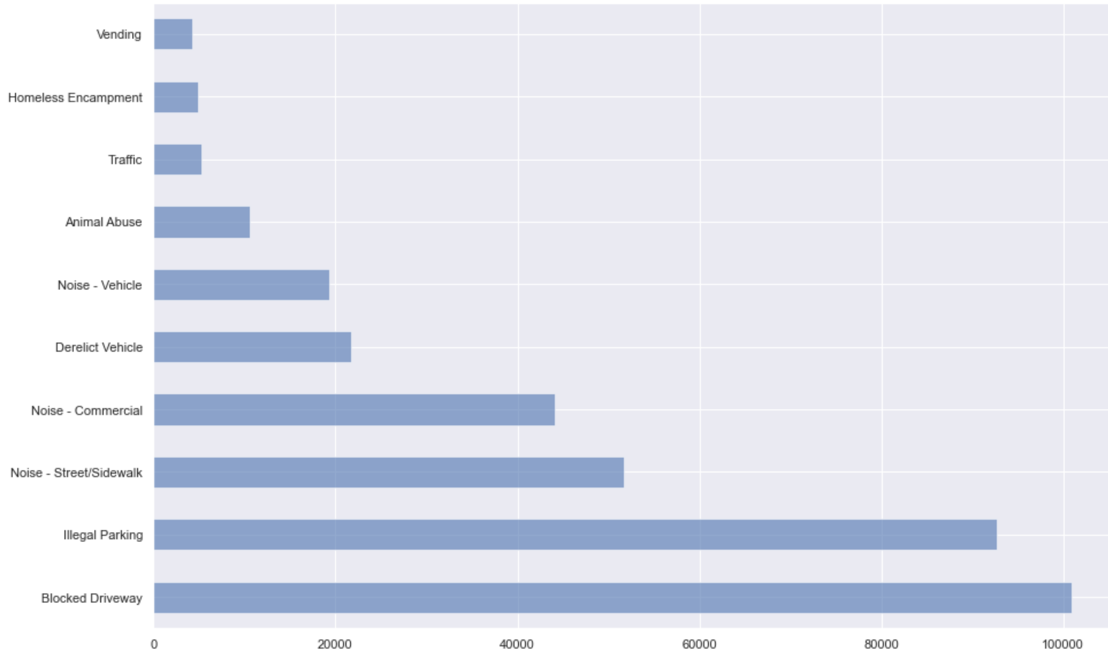
```
Total Number of Concerns :  364558

Percentage of Requests took less than 100 hour to get solved   :  33.63 %
Percentage of Requests took less than 1000 hour to get solved :  97.44 %
```

From above we can see that the data is heavily skewed. There are lots of outliers. Almost more than 97% of the requests are solved in less than 1000 hours i.e 17 days.

[11]:
```
#Univariate Distribution Plot for Request Closing Time
sns.distplot(df["Request_Closing_Time"])
plt.xlim((0,5000))
plt.ylim((0,0.0003))
plt.show()
```

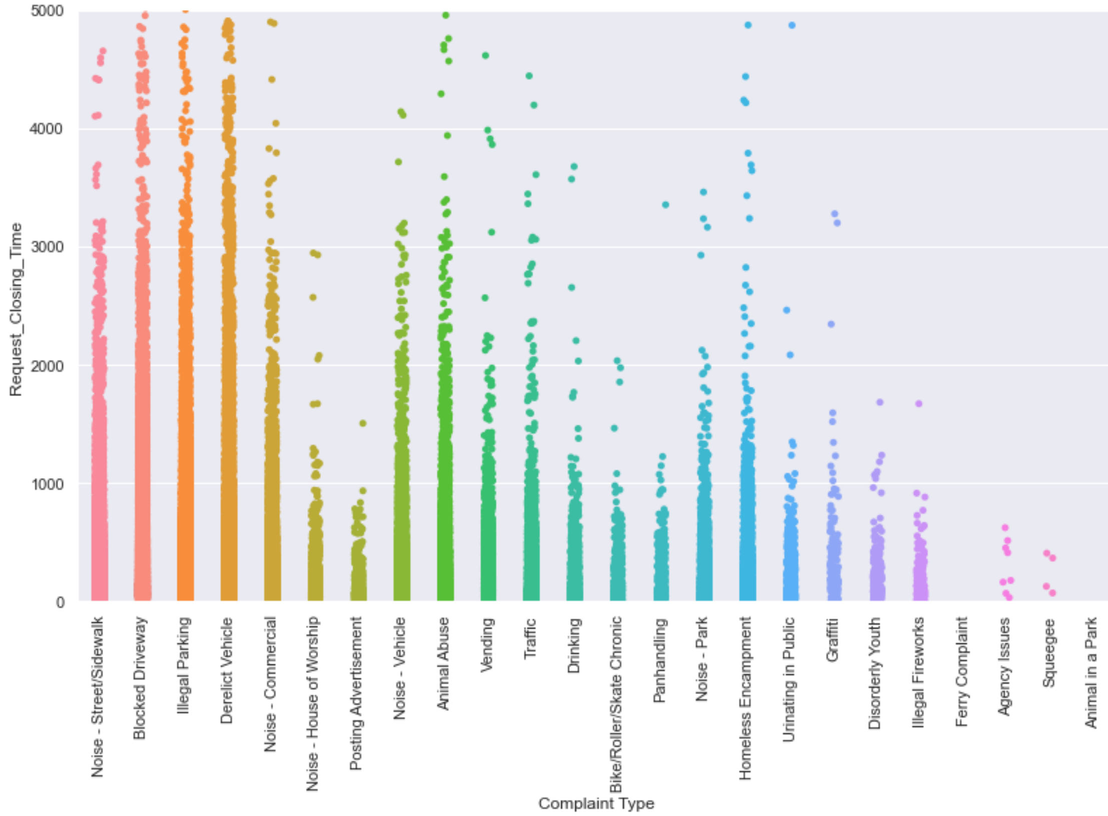


[12]:
```
# Count plot to understand the type of the complaint raised
df['Complaint Type'].value_counts()[:10].plot(kind='barh',alpha=0.
↪6,figsize=(15,10))
plt.show()
```



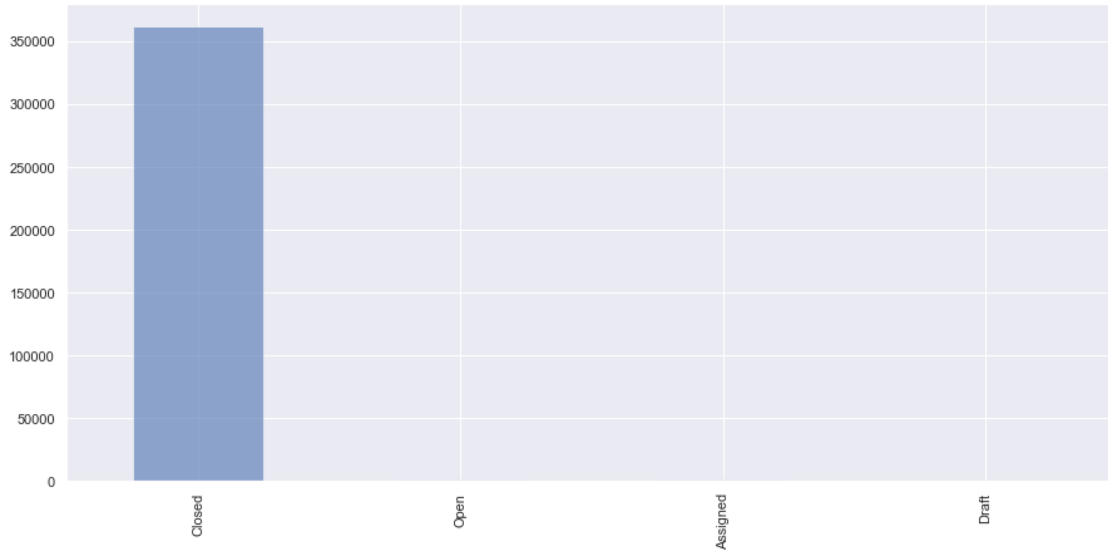
Almost around 85% of the the requests belongs to transport (Blocked driveway,Illegal Parking, Vehicle Noise, Road Traffic etc).

[13]:
```
#Categorical Scatter Plot to understand which type of complaints are taking␣
↪more time to get resolved
g=sns.catplot(x='Complaint Type', y="Request_Closing_Time",data=df)
g.fig.set_figwidth(15)
g.fig.set_figheight(7)
plt.xticks(rotation=90)
plt.ylim((0,5000))
plt.show()
```



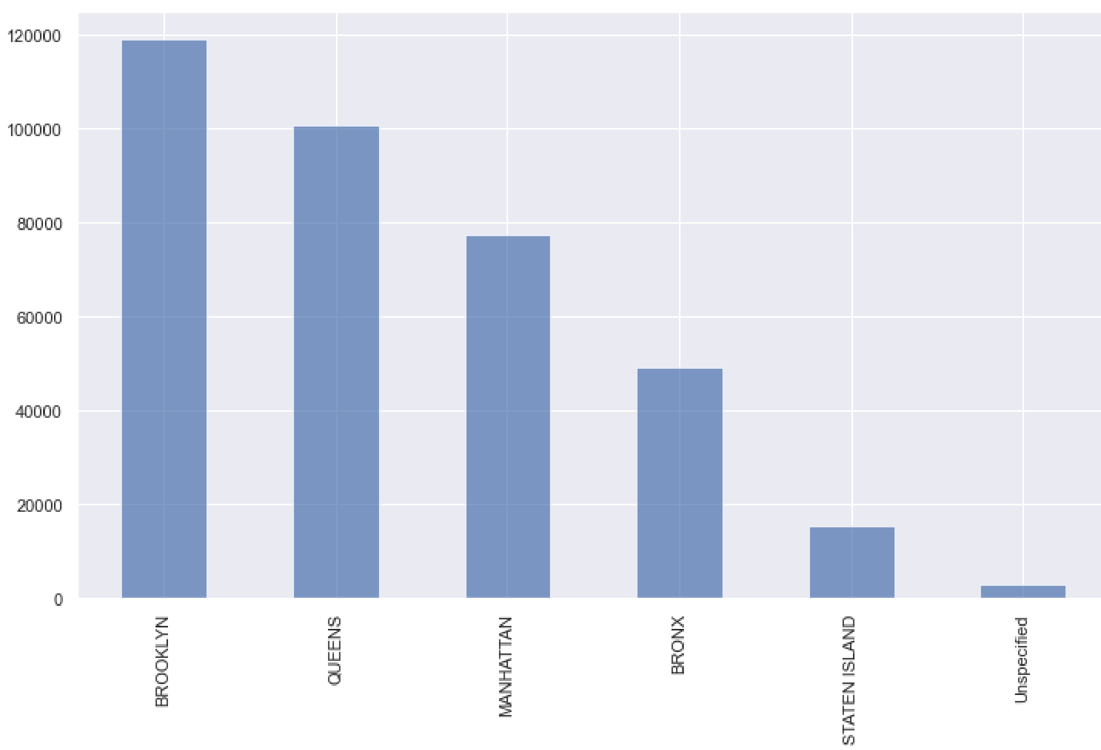
As we have got above that almost around 85% of the the requests belongs to transport (Blocked driveway,Illegal Parking, Vehicle Noise, Road Traffic etc). From this plot we can understand that most of these issues have taken more time to get resolved. Government should take measure in incresing awareness and find some measures to reduce traffic problems.

[14]:
```
# Count plot to know the status of the requests
df['Status'].value_counts().plot(kind='bar',alpha=0.6,figsize=(15,7))
plt.show()
```



As of now almost 98% of the cases are closed state.

[15]:
```
#Count Plot for Coloumn Borough
plt.figure(figsize=(12,7))
df['Borough'].value_counts().plot(kind='bar',alpha=0.7)
plt.show()
```



[16]:
```
#Percentage of cases in each Borough
for x in df["Borough"].unique():
    print("Percentage of Request from ",x," Division :␣
 ↪",round((df["Borough"]==x).sum()/len(df)*100,2))
```

```
Percentage of Request from  MANHATTAN  Division :  21.25
Percentage of Request from  QUEENS  Division :  27.64
Percentage of Request from  BRONX  Division :  13.49
Percentage of Request from  BROOKLYN  Division :  32.6
Percentage of Request from  Unspecified  Division :  0.81
Percentage of Request from  STATEN ISLAND  Division :  4.21
```

[17]:
```
#Unique Location Types
df["Location Type"].unique()
```

[17]:
```
array(['Street/Sidewalk', 'Club/Bar/Restaurant', 'Store/Commercial',
       'House of Worship', 'Residential Building/House',
       'Residential Building', 'Park/Playground', 'Vacant Lot',
       'House and Store', 'Highway', 'Commercial', 'Roadway Tunnel',
       'Subway Station', 'Parking Lot', 'Bridge', 'Terminal', nan,
       'Ferry', 'Park'], dtype=object)
```

[18]:
```
#Request Closing Time for all location Type sorted in ascending Order
pd.DataFrame(df.groupby("Location Type")["Request_Closing_Time"].mean()).
 ↪sort_values("Request_Closing_Time")
```

[18]:

Location Type	Request_Closing_Time
Subway Station	145.120000
Club/Bar/Restaurant	183.492218
House of Worship	190.052861
Store/Commercial	192.928792
Highway	204.372348
Park/Playground	206.594724
Bridge	229.458333
Street/Sidewalk	261.052945
Residential Building	267.260350
Commercial	270.649846
Roadway Tunnel	283.486047
House and Store	291.750204
Parking Lot	296.526747
Residential Building/House	300.233145
Vacant Lot	404.561930
Park	20210.566667
Ferry	NaN
Terminal	NaN

<p style-"color:red">We see that maximum(mean) time to resolve the complaint is taken in Park,Vacant Lot and Commercial areas whereas the cases in the Subway Station and Restaurent are resolved in very less time

[19]:
```python
#Request Closing Time for all City sorted in ascending Order
pd.DataFrame(df.groupby("City")["Request_Closing_Time"].mean()).
↪sort_values("Request_Closing_Time")
```

[19]:

City	Request_Closing_Time
ARVERNE	137.840605
ROCKAWAY PARK	139.602908
LITTLE NECK	155.031437
OAKLAND GARDENS	156.240167
BAYSIDE	160.062978
FAR ROCKAWAY	161.193068
NEW YORK	175.343723
FLUSHING	177.446478
FOREST HILLS	184.097636
WHITESTONE	187.976467
CORONA	188.984584
COLLEGE POINT	190.393782
JACKSON HEIGHTS	190.885368
ELMHURST	194.108392
FRESH MEADOWS	200.741045
REGO PARK	202.462138
BREEZY POINT	205.197849
EAST ELMHURST	206.801481
CENTRAL PARK	206.921364
STATEN ISLAND	228.038305
BROOKLYN	236.607935
Howard Beach	241.750000
Astoria	242.452302
Long Island City	245.388922
ASTORIA	265.236501
RIDGEWOOD	268.285547
SAINT ALBANS	271.040767
East Elmhurst	273.630556
Woodside	281.455622
KEW GARDENS	283.319775
JAMAICA	305.346459
SOUTH OZONE PARK	308.283046
SOUTH RICHMOND HILL	318.020470
WOODHAVEN	321.714469
RICHMOND HILL	321.749064
MIDDLE VILLAGE	323.290492
OZONE PARK	328.309146

```
MASPETH                     328.997706
HOLLIS                      332.061427
HOWARD BEACH                346.959615
BRONX                       353.116425
LONG ISLAND CITY            367.326726
SUNNYSIDE                   380.744297
WOODSIDE                    389.758733
NEW HYDE PARK               423.396512
GLEN OAKS                   501.653463
SPRINGFIELD GARDENS         510.113239
CAMBRIA HEIGHTS             542.883117
ROSEDALE                    569.194745
BELLEROSE                   576.173614
QUEENS VILLAGE              593.920472
FLORAL PARK                 609.812160
QUEENS                      717.171171
```

Handling Missing Values

[20]:
```
#Percentage Of Missing Value
pd.DataFrame((df.isnull().sum()/df.shape[0]*100)).
 ↪sort_values(0,ascending=False)[:20]
```

[20]:
```
                                      0
School or Citywide Complaint  100.000000
Garage Lot Name               100.000000
Vehicle Type                  100.000000
Taxi Pick Up Location         100.000000
Taxi Company Borough          100.000000
Ferry Direction                99.999726
Ferry Terminal Name            99.999451
Road Ramp                      99.928132
Bridge Highway Segment         99.928132
Bridge Highway Direction       99.918531
Bridge Highway Name            99.918531
Landmark                       99.897136
Intersection Street 2          86.144317
Intersection Street 1          85.977540
Cross Street 2                 15.856187
Cross Street 1                 15.686941
Street Name                    14.181283
Incident Address               14.181283
Descriptor                      1.783255
Latitude                        1.105448
```

We see that all the data related to school columns are empty which must be because none of the request or complaint are from the school sector. Thus we can go on and remove that column.

[21]:
```
#Remove the column with very high percentage of missing value
new_df=df.loc[:,(df.isnull().sum()/df.shape[0]*100)<=50]
```

[22]:
```
print("Old DataFrame Shape :",df.shape)
print("New DataFrame Shape : ",new_df.shape)
```

```
Old DataFrame Shape : (364558, 54)
New DataFrame Shape :  (364558, 40)
```

[23]:
```
rem=[]
for x in new_df.columns.tolist():
    if new_df[x].nunique()<=3:
        print(x+ " "*10+" : ",new_df[x].unique())
        rem.append(x)
```

```
Agency           :  ['NYPD']
Agency Name           :  ['New York City Police Department' 'NYPD' 'Internal
Affairs Bureau']
Facility Type           :  ['Precinct' nan]
Park Facility Name           :  ['Unspecified' 'Alley Pond Park - Nature
Center']
School Name           :  ['Unspecified' 'Alley Pond Park - Nature Center']
School Number           :  ['Unspecified' 'Q001']
School Region           :  ['Unspecified' nan]
School Code           :  ['Unspecified' nan]
School Phone Number           :  ['Unspecified' '7182176034']
School Address           :  ['Unspecified' 'Grand Central Parkway, near the
soccer field']
School City           :  ['Unspecified' 'QUEENS']
School State           :  ['Unspecified' 'NY']
School Zip           :  ['Unspecified' nan]
School Not Found           :  ['N']
```

We see that all the data above have not much details, are Unspecified. So we can remove those columns to ease our analysis

[24]:
```
new_df.drop(rem,axis=1,inplace=True)
```

[25]:
```
new_df.shape
```

[25]:
```
(364558, 26)
```

[26]:
```
#Remove columns that are not needed for our analysis
rem1=["Unique Key","Incident Address","Descriptor","Street Name","Cross Street␣
↪1","Cross Street 2","Due Date","Resolution Description","Resolution Action␣
↪Updated Date","Community Board","X Coordinate (State Plane)","Y Coordinate␣
↪(State Plane)","Park Borough","Latitude","Longitude","Location"]

new_df.drop(rem1,axis=1,inplace=True)
```

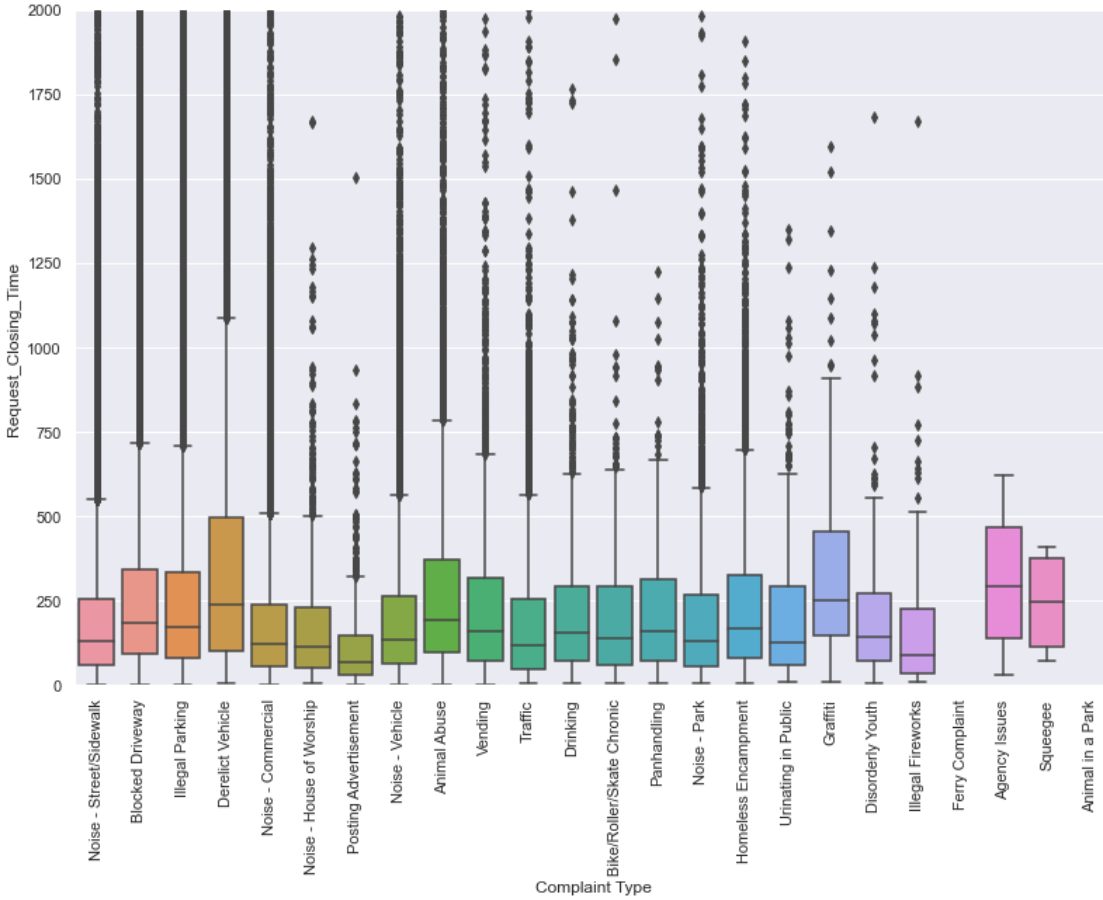
[27]:
```
new_df.head()
```

[27]:
```
         Created Date         Closed Date           Complaint Type  \
0 2015-12-31 23:59:45 2016-01-01 00:55:15  Noise - Street/Sidewalk
1 2015-12-31 23:59:44 2016-01-01 01:26:57         Blocked Driveway
2 2015-12-31 23:59:29 2016-01-01 04:51:03         Blocked Driveway
3 2015-12-31 23:57:46 2016-01-01 07:43:13          Illegal Parking
4 2015-12-31 23:56:58 2016-01-01 03:24:42          Illegal Parking

     Location Type  Incident Zip Address Type      City  Status    Borough  \
0  Street/Sidewalk       10034.0      ADDRESS  NEW YORK  Closed  MANHATTAN
1  Street/Sidewalk       11105.0      ADDRESS   ASTORIA  Closed     QUEENS
2  Street/Sidewalk       10458.0      ADDRESS     BRONX  Closed      BRONX
3  Street/Sidewalk       10461.0      ADDRESS     BRONX  Closed      BRONX
4  Street/Sidewalk       11373.0      ADDRESS  ELMHURST  Closed     QUEENS

   Request_Closing_Time
0             55.500000
1             87.216667
2            291.566667
3            465.450000
4            207.733333
```

Hypothesis Testing

[28]:
```
g=sns.catplot(x="Complaint Type",y="Request_Closing_Time",kind="box",data=new_df)
g.fig.set_figheight(8)
g.fig.set_figwidth(15)
plt.xticks(rotation=90)
plt.ylim((0,2000))
```

[28]:
```
(0.0, 2000.0)
```



H0 : there is no significant different in mean of Request_Closing_Time for different Complaint

H1 : there is signficant different in mean of Request_Closing_Time for different Complaint

[29]:
```
anova_df=pd.DataFrame()
anova_df["Request_Closing_Time"]=new_df["Request_Closing_Time"]
anova_df["Complaint"]=new_df["Complaint Type"]

anova_df.dropna(inplace=True)
anova_df.head()
```

[29]:

	Request_Closing_Time	Complaint
0	55.500000	Noise - Street/Sidewalk
1	87.216667	Blocked Driveway
2	291.566667	Blocked Driveway
3	465.450000	Illegal Parking
4	207.733333	Illegal Parking

[30]:
```
lm=ols("Request_Closing_Time~Complaint",data=anova_df).fit()
table=sm.stats.anova_lm(lm)
table
```

[30]:

	df	sum_sq	mean_sq	F	PR(>F)
Complaint	22.0	1.487316e+09	6.760526e+07	565.26157	0.0
Residual	362154.0	4.331361e+10	1.196000e+05	NaN	NaN

Since p value for the Complaint is less that 0.01 thus we accept alternate hypothesis i.e there is significant difference in the mean response time w.r.t different type of complaint.

H0 : Complaint Type and Location Type are independent

H1 : Complaint Type and Location Type are related

[31]:
```
chi_sq=pd.DataFrame()
chi_sq["Location Type"]=new_df["Location Type"]
chi_sq["Complaint Type"]=new_df["Complaint Type"]

chi_sq.dropna(inplace=True)
```

[32]:
```
data_crosstab = pd.crosstab( chi_sq["Location Type"],chi_sq["Complaint Type"])
```

[33]:
```
stat, p, dof, expected = chi2_contingency(data_crosstab)

alpha = 0.05
if p <= alpha:
    print('Dependent (reject H0)')
else:
    print('Independent (H0 holds true)')
```

```
Dependent (reject H0)
```

Since p value for the chi square test is less than 0.05(LOS) we can conclude that Complaint Type is dependent on Location Type i.e specific type of complaint is raised from specific places,

[ ]:
```

```

[ ]:
```

```