Customer Service Requests Analysis

September 3, 2022

[1]:
```python
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
```

[2]:
```python
df=pd.read_csv("311_Service_Requests_from_2010_to_Present.csv")
df.head()
```

[2]:
```
   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]
```

[3]:
```
df.describe()
```

[3]:
```
         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
```

[4]:
```
df.shape
```

[4]:
```
(364558, 53)
```

[5]:
```
# Converting the data into datetime format
df["Created Date"]=pd.to_datetime(df["Created Date"])
df["Closed Date"]=pd.to_datetime(df["Closed Date"])
```

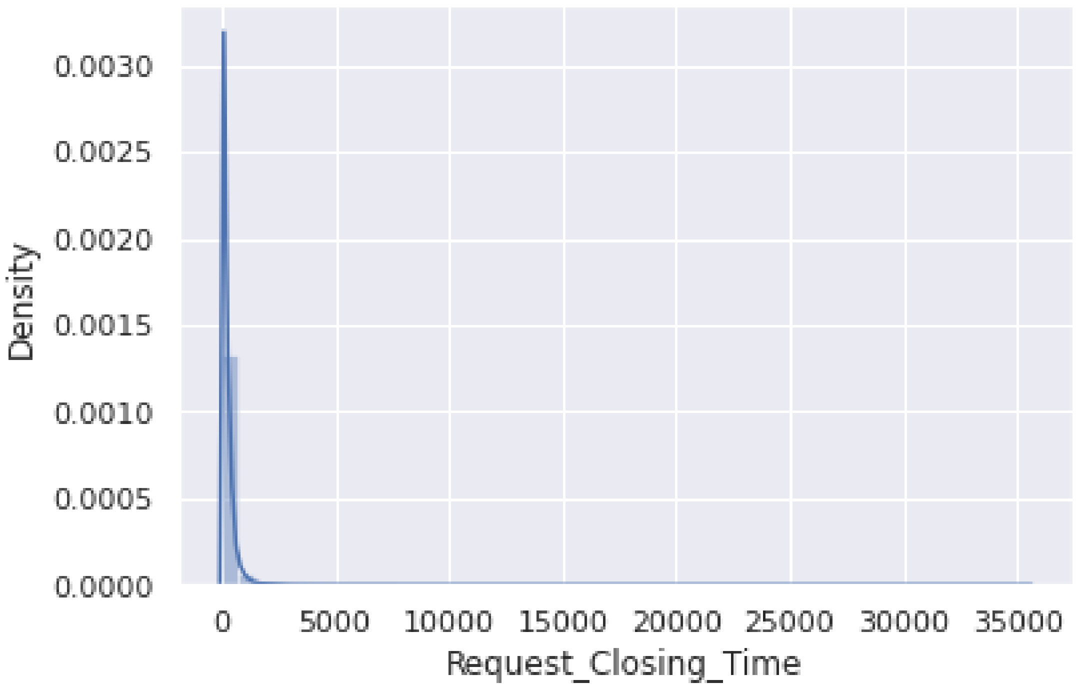
[6]:
```
#Creating the new column that consist the amount of time taken to resolve the␣
 ↪complaint
df["Request_Closing_Time"]=(df["Closed Date"]-df["Created Date"])

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
```

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

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

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

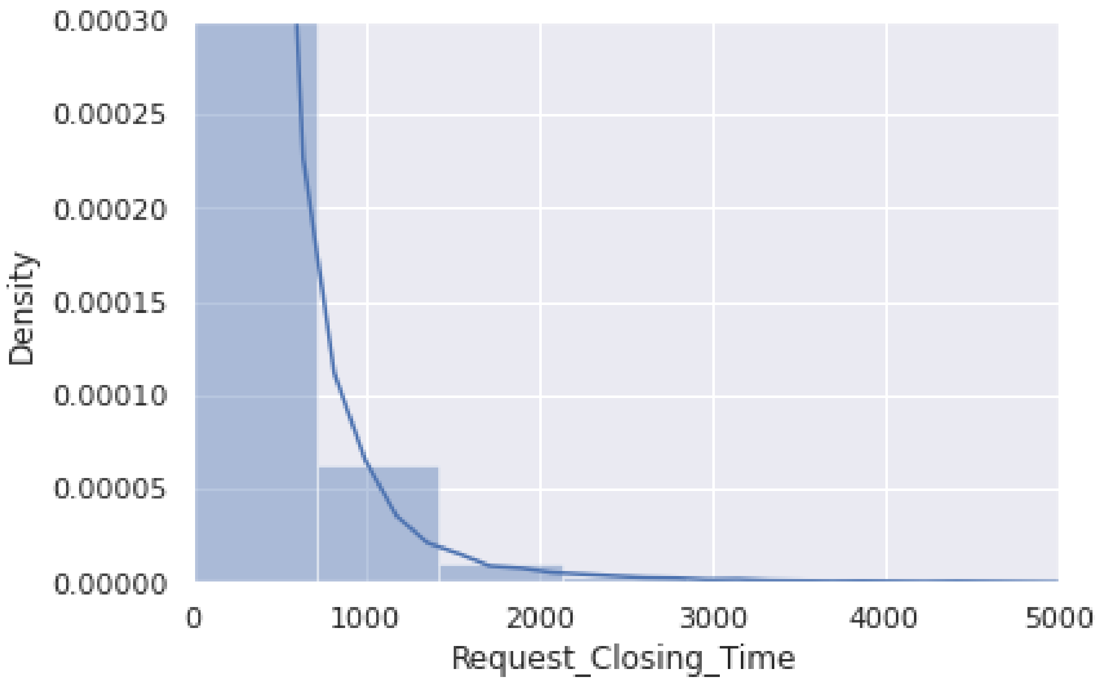
```
[9]: <function matplotlib.pyplot.show(close=None, block=None)>
```



```
[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 %
```

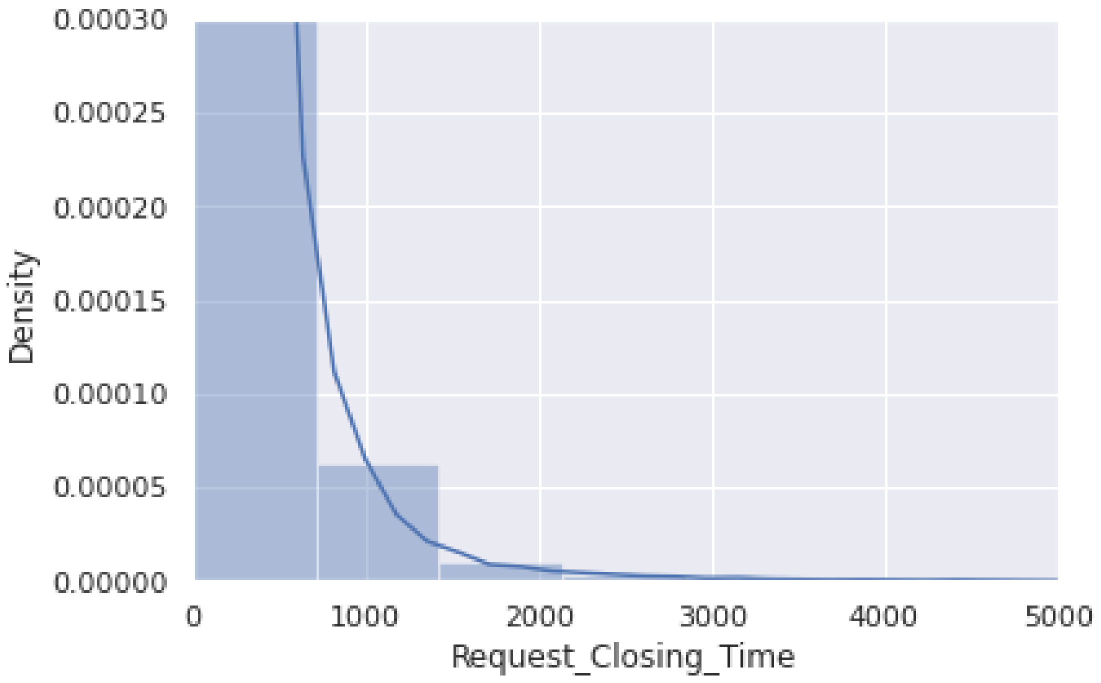
```
[11]: #Univariate Distribution Plot for Request Closing Time
      sns.distplot(df["Request_Closing_Time"])
      plt.xlim((0,5000))
      plt.ylim((0,0.0003))
      plt.show()
```



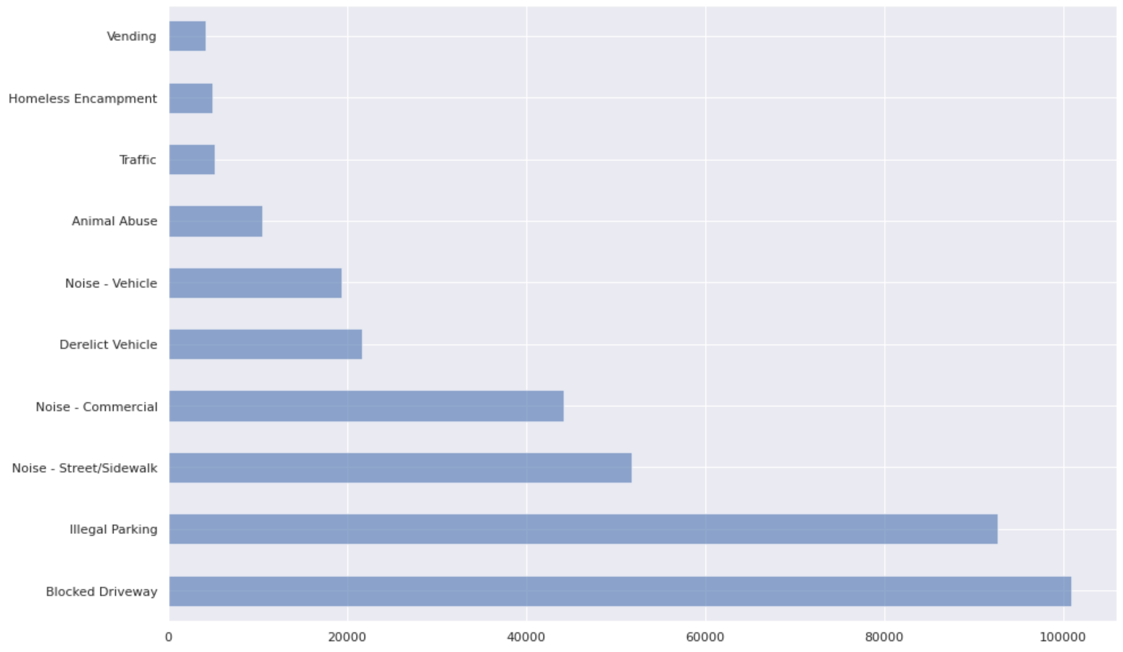
[12]:
```
print("Total Number of Concerns : ",len(df),"\n")
print("Percentage of Requests took less than 100 hour to get solved   :␣
 ↪",round((len(df)-(df["Request_Closing_Time"]>100).sum())/len(df)*100,2),"%")
print("Percentage of Requests took less than 1000 hour to get solved :␣
 ↪",round((len(df)-(df["Request_Closing_Time"]>1000).sum())/len(df)*100,2),"%")
```

```
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 %
```

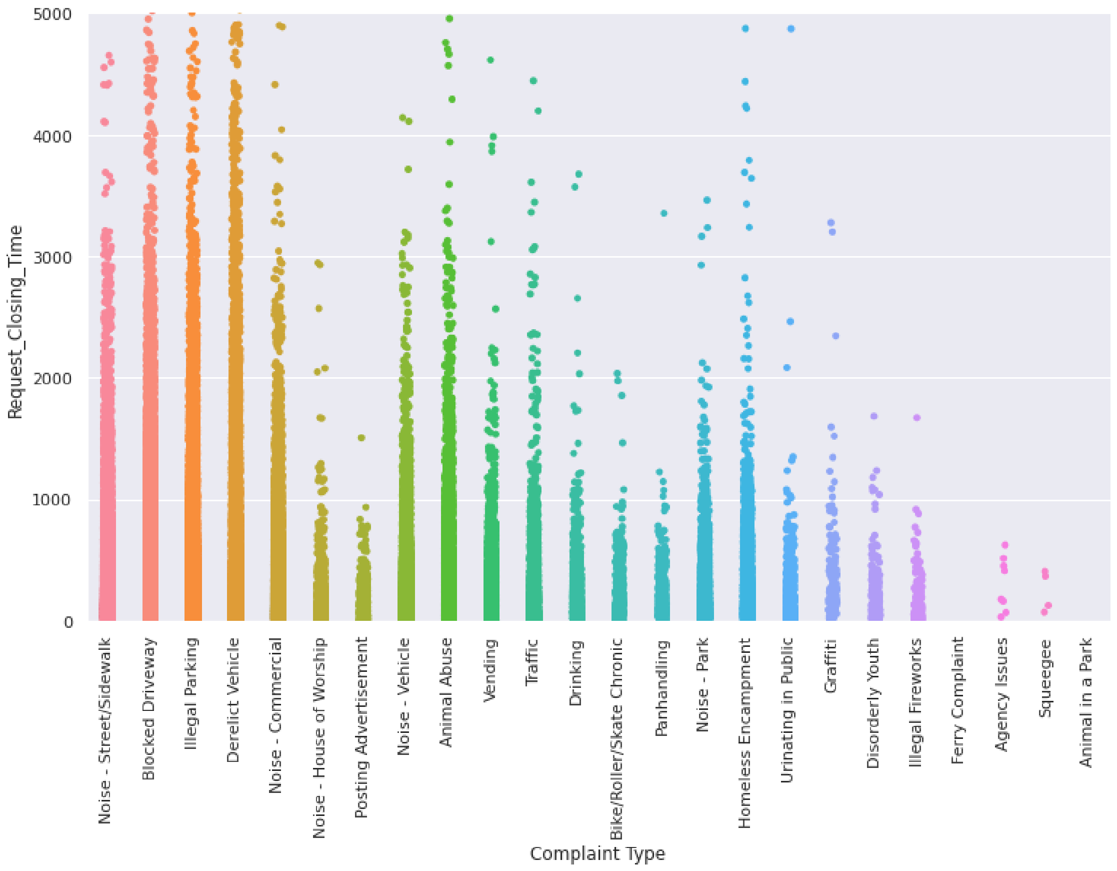
[13]:
```
#Univariate Distribution Plot for Request Closing Time
sns.distplot(df["Request_Closing_Time"])
plt.xlim((0,5000))
plt.ylim((0,0.0003))
plt.show()
```



[14]:
```
# 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()
```

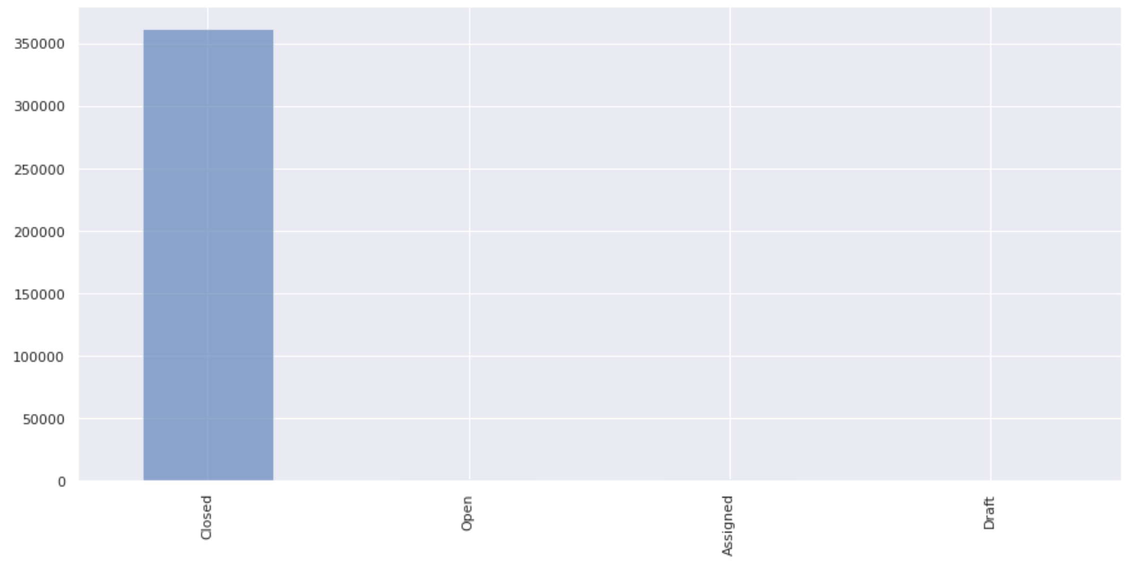


[15]:
```
#Categorical Scatter Plot to understand which type of complaints are taking␣
↪more time to get resolved
g=sns.catplot(x='Complaint Type', y="Request_Closing_Time",data=df)
g.fig.set_figwidth(15)
g.fig.set_figheight(7)
plt.xticks(rotation=90)
plt.ylim((0,5000))
plt.show()
```

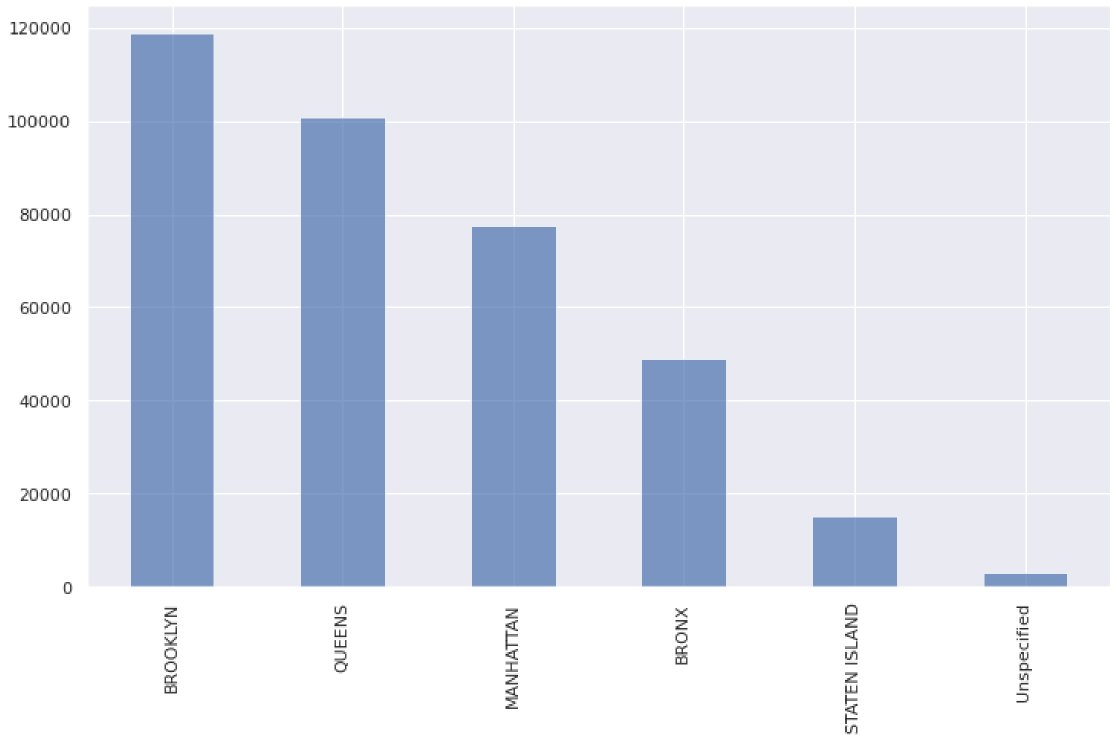


[16]:
```
#As we have got above that almost around 85% of the the requests belongs to␣
↪transport (Blocked driveway,Illegal Parking, Vehicle Noise, Road Traffic etc␣
↪). From this plot we can understand that most of these issues have taken␣
↪more time to get resolved. Government should take measure in incresing␣
↪awareness and find some measures to reduce traffic problems.
```

[17]:
```
# Count plot to know the status of the requests
df['Status'].value_counts().plot(kind='bar',alpha=0.6,figsize=(15,7))
plt.show()
```



[18]:
```
#Count Plot for Coloumn Borough
plt.figure(figsize=(12,7))
df['Borough'].value_counts().plot(kind='bar',alpha=0.7)
plt.show()
```



[19]:
```
#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
```

[20]:
```
#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")
```

[20]:
```
                            Request_Closing_Time
Location Type
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
```

[21]:
```
#Request Closing Time for all City sorted in ascending Order
pd.DataFrame(df.groupby("City")["Request_Closing_Time"].mean()).
 ↪sort_values("Request_Closing_Time")
```

[21]:
```
                     Request_Closing_Time
City
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
```

[22]:
```
#Percentage Of Missing Value
pd.DataFrame((df.isnull().sum()/df.shape[0]*100)).
 ↪sort_values(0,ascending=False)[:20]
```

[22]:
```
                                             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
```

[23]:
```
#Remove the column with very high percentage of missing value
new_df=df.loc[:,(df.isnull().sum()/df.shape[0]*100)<=50]
```

[24]:
```
print("Old DataFrame Shape :",df.shape)
print("New DataFrame Shape : ",new_df.shape)
```

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

[25]:
```
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']
```

[26]:
```
new_df.drop(rem,axis=1,inplace=True)
```

[27]:
```
new_df.shape
```

[27]:
```
(364558, 26)
```

[28]:
```
#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)
```

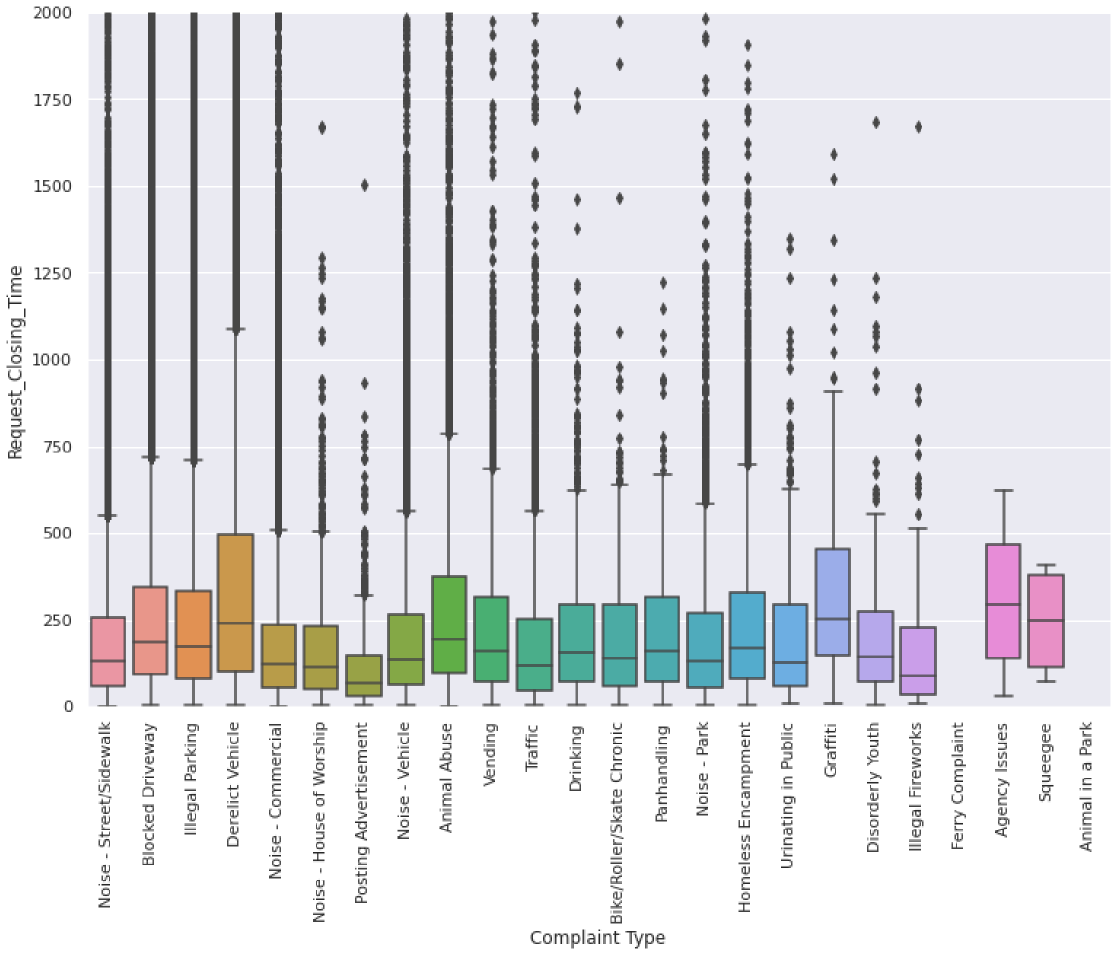
[29]:
```
new_df.head()
```

[29]:
```
          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
```

[30]:
```
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))
```

[30]:
```
(0.0, 2000.0)
```



[31]:
```
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()
```

[31]:

```
   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
```

[32]:

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

[32]:

```
                 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
```

[33]:

```
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)
```

[34]:

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

[35]:

```
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)
```

[36]:

```
#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,
```

[ ]: