```
#Importing the libraries
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

#Loading the data
df = pd.read_csv('311_Service_Requests_from_2010_to_Present.csv')
df.head()
```

```
   Unique Key            Created Date    Closed Date Agency  \
0    32310363  12/31/2015 11:59:45 PM  01-01-16 0:55   NYPD
1    32309934  12/31/2015 11:59:44 PM  01-01-16 1:26   NYPD
2    32309159  12/31/2015 11:59:29 PM  01-01-16 4:51   NYPD
3    32305098  12/31/2015 11:57:46 PM  01-01-16 7:43   NYPD
4    32306529  12/31/2015 11:56:58 PM  01-01-16 3:24   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]
```

```
#Descriptive Analysis

print(df.shape)

df.describe()
```

```
(300698, 53)

         Unique Key   Incident Zip  X Coordinate (State Plane)  \
count  3.006980e+05  298083.000000                2.971580e+05
mean   3.130054e+07   10848.888645                1.004854e+06
std    5.738547e+05     583.182081                2.175338e+04
min    3.027948e+07      83.000000                9.133570e+05
25%    3.080118e+07   10310.000000                9.919752e+05
50%    3.130436e+07   11208.000000                1.003158e+06
75%    3.178446e+07   11238.000000                1.018372e+06
max    3.231065e+07   11697.000000                1.067173e+06

       Y Coordinate (State Plane)  School or Citywide Complaint
Vehicle Type  \
count               297158.000000                           0.0
0.0
```

```
mean                203754.534416                          NaN
NaN
std                  29880.183529                          NaN
NaN
min                 121219.000000                          NaN
NaN
25%                 183343.000000                          NaN
NaN
50%                 201110.500000                          NaN
NaN
75%                 224125.250000                          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  297158.000000  297158.000000
mean       40.725885     -73.925630
std         0.082012       0.078454
min        40.499135     -74.254937
25%        40.669796     -73.972142
50%        40.718661     -73.931781
75%        40.781840     -73.876805
max        40.912869     -73.700760
```

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.

```
#Convert data into datetime format
df['Created Date'] = pd.to_datetime(df['Created Date'])
df['Closed Date'] = pd.to_datetime(df['Closed Date'])
df.head()

   Unique Key        Created Date         Closed Date Agency  \
0    32310363 2015-12-31 23:59:45 2016-01-01 00:55:00   NYPD
1    32309934 2015-12-31 23:59:44 2016-01-01 01:26:00   NYPD
2    32309159 2015-12-31 23:59:29 2016-01-01 04:51:00   NYPD
3    32305098 2015-12-31 23:57:46 2016-01-01 07:43:00   NYPD
4    32306529 2015-12-31 23:56:58 2016-01-01 03:24:00   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]
```

```
#Creating a new columns that consist the total 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
```

```
# Exploratory Data Analysis
```

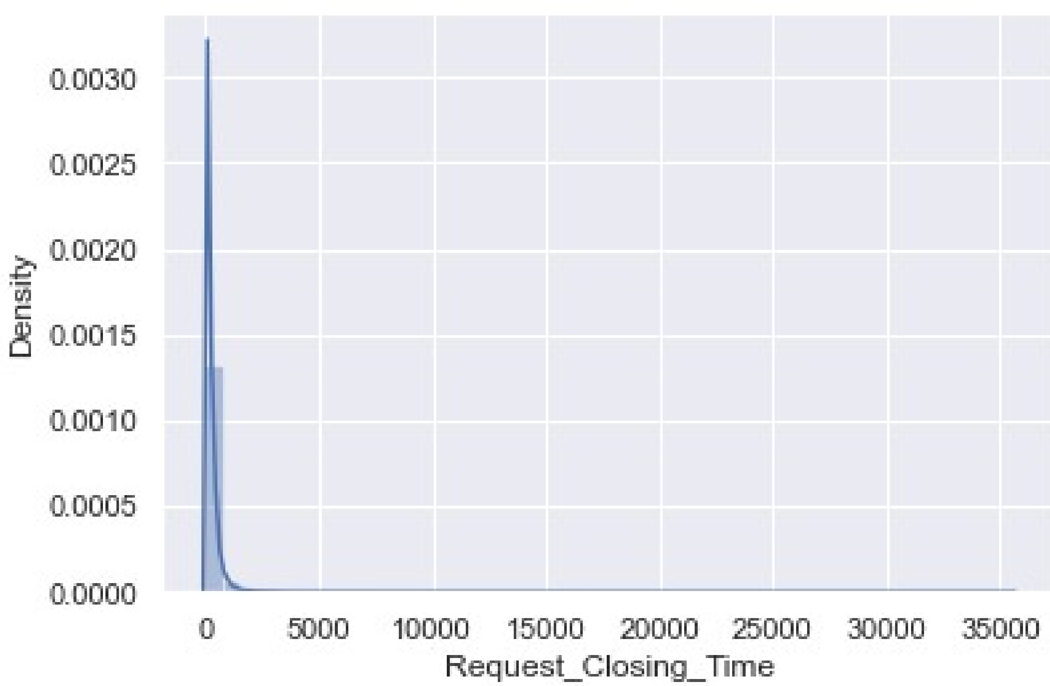
```
df['Agency'].unique()
```

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

```
#All our data belongs to a single department of NYPD
```

```
#Univariate Distribution for Request closing time
sns.distplot(df['Request_Closing_Time'])
plt.show
```

```
<function matplotlib.pyplot.show(close=None, block=None)>
```



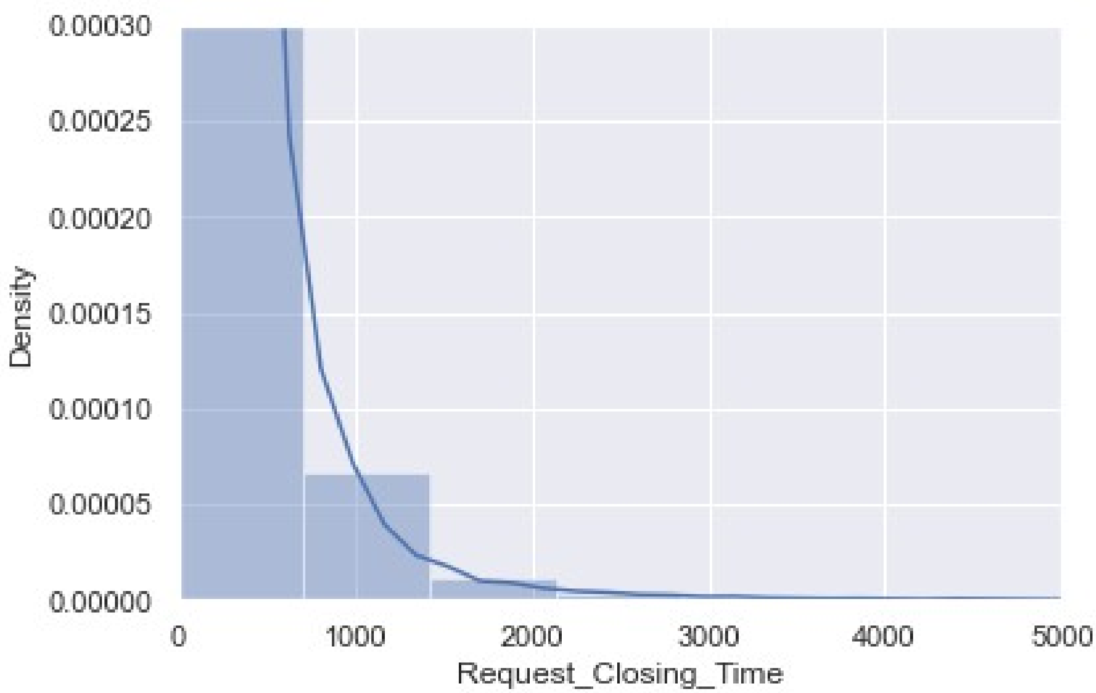

```
print('Total number of concerns:',len(df),'/n')
print('Percent of requests took less than 100 hours to get solved:',
```

```
round((len(df)-(df['Request_Closing_Time']>100).sum())/len(df)*100,2),
'%')
print('Percent of requests took less than 1000 hours to get solved:',
round((len(df)-(df['Request_Closing_Time']>1000).sum())/len(df)*100,2)
,'%')
```

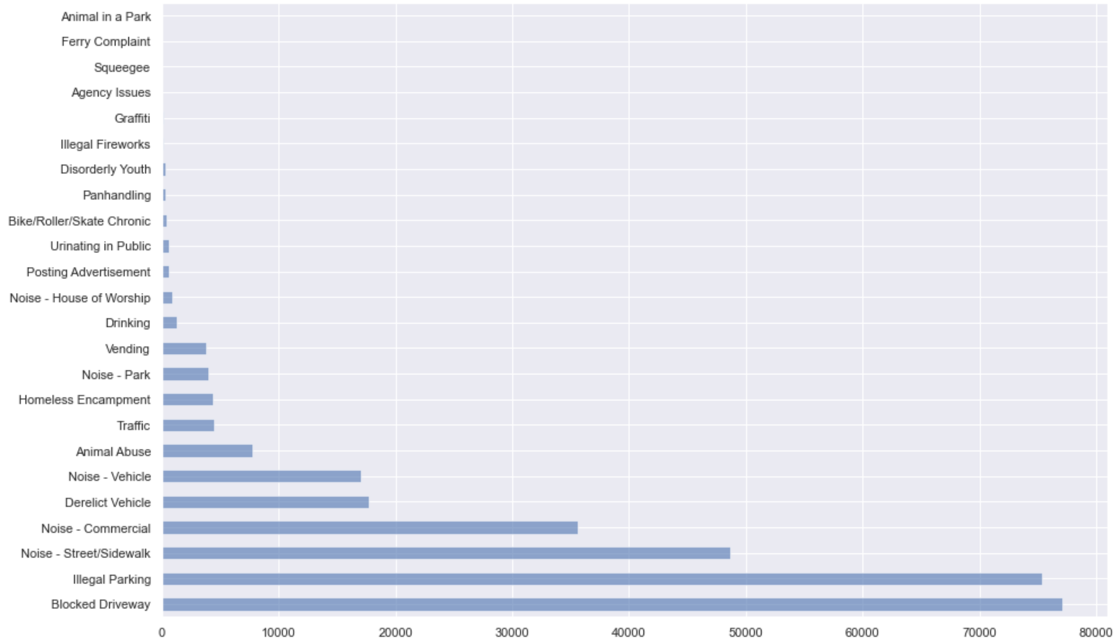
```
Total number of concerns: 300698 /n
Percent of requests took less than 100 hours to get solved: 33.32 %
Percent of requests took less than 1000 hours to get solved: 97.19 %
```

From the above we can see the data is heavily skewed. There are a lot of outliers. Almost 97% of the requests are solved within 1000 hours i.e 17 days

```
#Univariate Distribution for Request closing time
sns.distplot(df['Request_Closing_Time'])
plt.xlim((0,5000))
plt.ylim((0,0.0003))
plt.show()
```

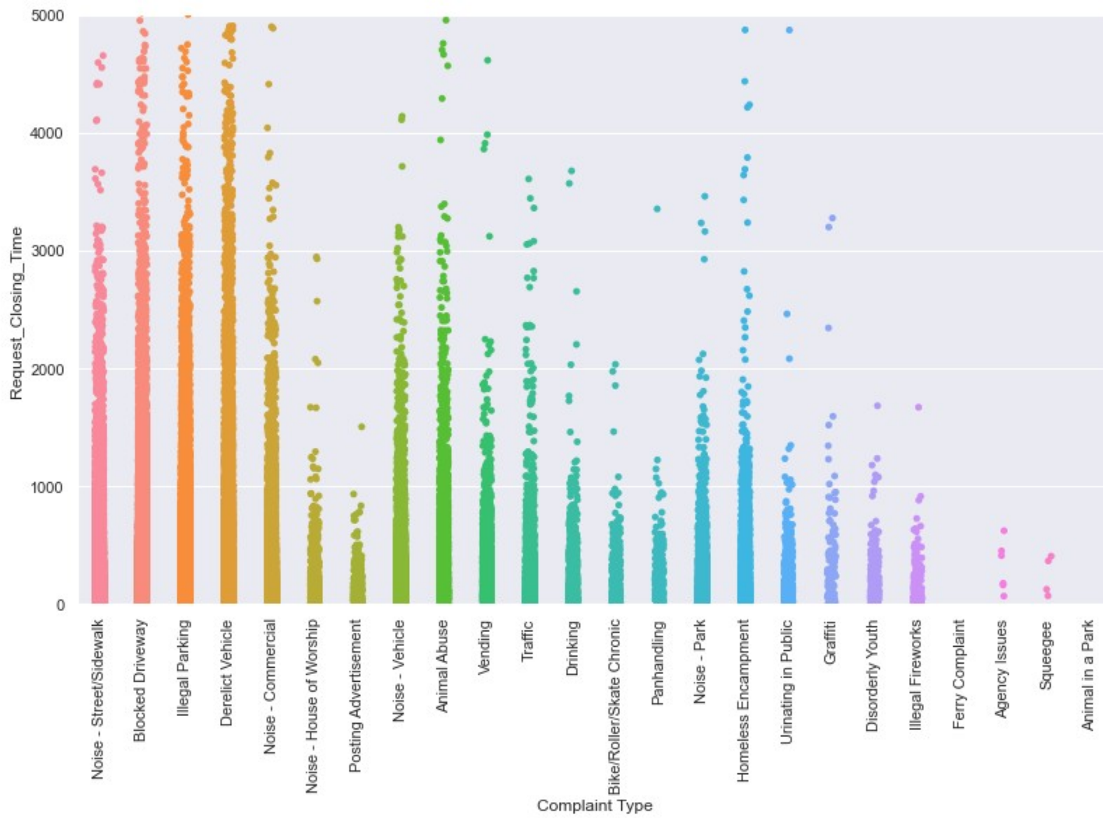



```
#Count Plot to understand the type of complaints raised
df['Complaint
Type'].value_counts().plot(kind='barh',alpha=0.6,figsize=(15,10))
plt.show()
```



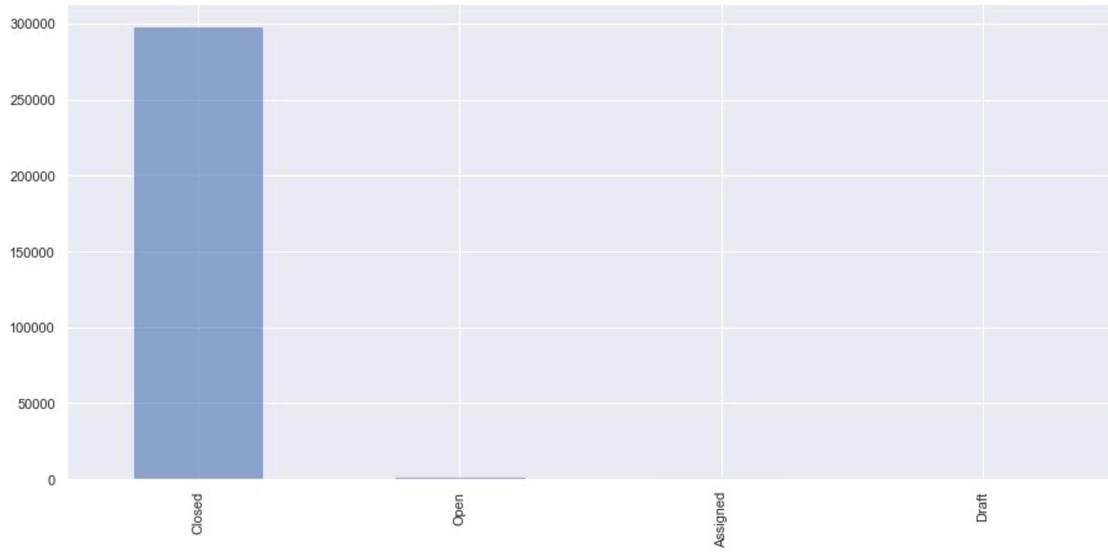
Almost around 85% of the the requests belongs to transport (Blocked driveway, illegal parking, vehicle noise, road traffic etc).

```
#Categorical scatter plot to understand which type of complaints are
taking more time to get resolved
p=sns.catplot(x='Complaint Type', y='Request_Closing_Time', data=df)
p.fig.set_figwidth(15)
p.fig.set_figheight(7)
plt.xticks(rotation=90)
plt.ylim((0,5000))
plt.show()
```



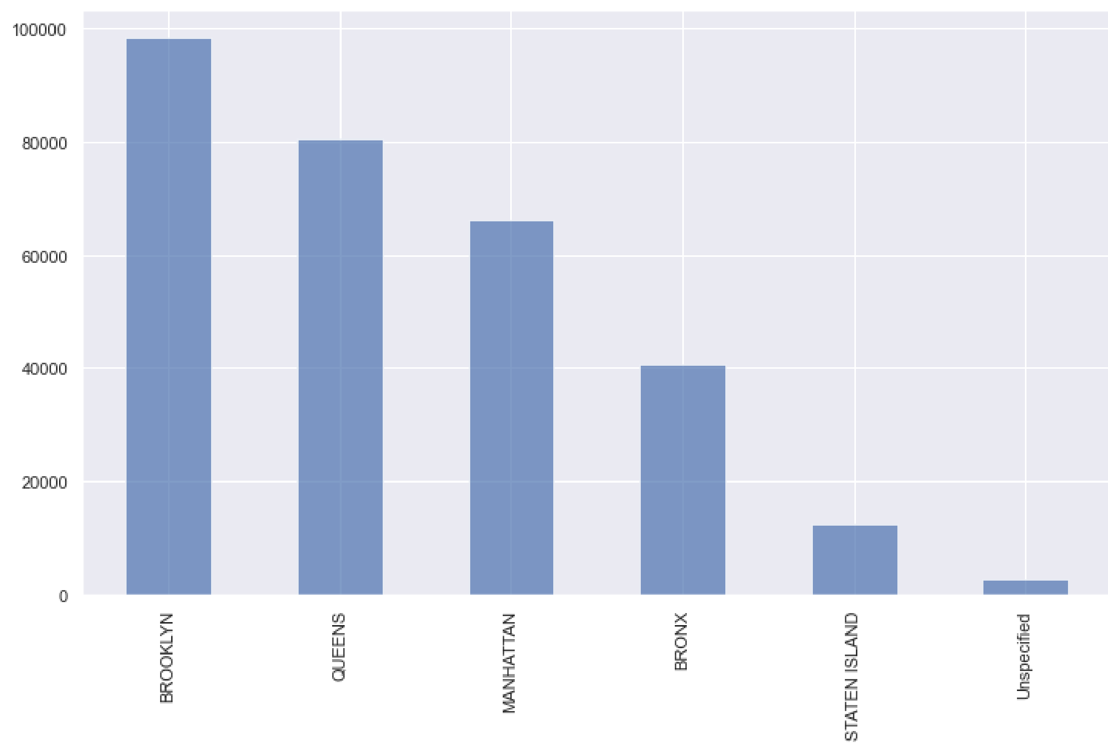
As we have got above that almost around 85% of the the requests belongs to transport (Blocked driveway,Illegal Parking, Vehicle Noise, Road Traffic etc). From this plot we can understand that most of these issues have taken more time to get resolved. Government should take measure in incresing awareness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

```
#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 98% of the cases are closed.

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




```
#Percentage of cases in each Borough
for x in df['Borough'].unique():
    print('Percentage of requests from', x, 'division:',
round((df['Borough']==x).sum()/len(df)*100,2))
```

```
Percentage of requests from MANHATTAN division: 21.99
Percentage of requests from QUEENS division: 26.82
Percentage of requests from BRONX division: 13.54
Percentage of requests from BROOKLYN division: 32.69
Percentage of requests from Unspecified division: 0.86
Percentage of requests from STATEN ISLAND division: 4.1
```

```
#Unique location types
df['Location Type'].unique()
```

```
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)
```

```
#Request closing time for all location type in ascending order
pd.DataFrame(df.groupby('Location Type')
['Request_Closing_Time'].mean()).sort_values('Request_Closing_Time')
```

```
                            Request_Closing_Time
Location Type
Subway Station                        142.250980
Club/Bar/Restaurant                   186.074330
House of Worship                      191.833279
Store/Commercial                      198.089073
Park/Playground                       207.137129
Highway                               223.424221
Bridge                                229.158333
Roadway Tunnel                        266.525714
Street/Sidewalk                       268.515306
Residential Building                  289.089941
House and Store                       300.795699
Residential Building/House            309.505679
Parking Lot                           320.130342
Commercial                            320.566129
Vacant Lot                            448.435498
Park                                20210.083333
Ferry                                        NaN
Terminal                                     NaN
```

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

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

City	Request_Closing_Time
ARVERNE	135.895606
ROCKAWAY PARK	139.133736
LITTLE NECK	154.660316
OAKLAND GARDENS	157.853146
BAYSIDE	160.759992
FAR ROCKAWAY	167.399774
NEW YORK	178.357371
FLUSHING	181.081826
FOREST HILLS	193.449032
CORONA	193.670512
WHITESTONE	194.688843
FRESH MEADOWS	195.843207
COLLEGE POINT	196.417842
JACKSON HEIGHTS	196.419964
CENTRAL PARK	197.658591
ELMHURST	198.631095
REGO PARK	207.665668
BREEZY POINT	209.789444
EAST ELMHURST	214.659709
STATEN ISLAND	232.796699
Howard Beach	241.750000
BROOKLYN	242.878848
Long Island City	246.045522
Astoria	251.076304
RIDGEWOOD	266.507613
ASTORIA	275.934779
SAINT ALBANS	283.252098
KEW GARDENS	302.578556
Woodside	312.083333
JAMAICA	312.606051
SOUTH OZONE PARK	319.678662
MIDDLE VILLAGE	323.097583
RICHMOND HILL	329.658614
WOODHAVEN	335.728705
MASPETH	335.985805
SOUTH RICHMOND HILL	337.049201
OZONE PARK	340.863702
HOLLIS	345.610161
East Elmhurst	362.867857
BRONX	365.769723
HOWARD BEACH	369.652291
LONG ISLAND CITY	392.351457
SUNNYSIDE	411.120332
WOODSIDE	413.606029
NEW HYDE PARK	453.365646
GLEN OAKS	528.943900
SPRINGFIELD GARDENS	551.145130
ROSEDALE	601.867552

```
CAMBRIA HEIGHTS                 607.426555
BELLEROSE                       633.386578
QUEENS VILLAGE                  654.411273
FLORAL PARK                     703.171272
QUEENS                          815.586458
```

Handling Missing Values

```
#Percentage of missing values
pd.DataFrame((df.isnull().sum()/df.shape[0]*100)).sort_values(0,ascend
ing=False)[: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                  99.999667
Ferry Terminal Name              99.999335
Road Ramp                        99.929165
Bridge Highway Segment           99.929165
Bridge Highway Direction         99.919188
Bridge Highway Name              99.919188
Landmark                         99.883937
Intersection Street 2            85.579552
Intersection Street 1            85.414602
Cross Street 2                   16.554483
Cross Street 1                   16.388203
Street Name                      14.768971
Incident Address                 14.768971
Descriptor                        1.966757
Latitude                          1.177261
```

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.

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

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

```
Old DataFrame Shape : (300698, 54)
New DataFrame Shape :  (300698, 40)
```

```
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']
```

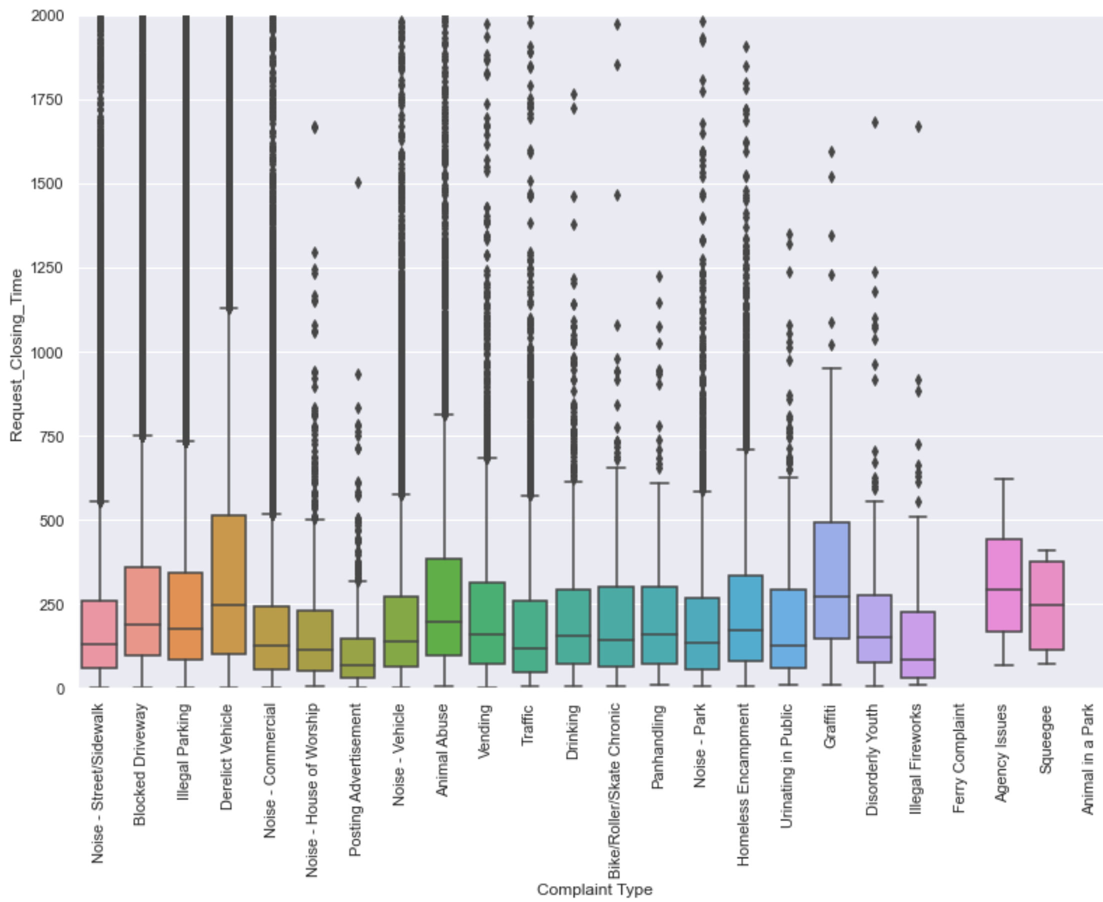
We see that all the data above have not much details, are Unspecified. So we can remove those columns to ease our analysis

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

new_df.shape

(300698, 26)

new_df.head()

   Unique Key        Created Date         Closed Date  \
0    32310363 2015-12-31 23:59:45 2016-01-01 00:55:00
1    32309934 2015-12-31 23:59:44 2016-01-01 01:26:00
2    32309159 2015-12-31 23:59:29 2016-01-01 04:51:00
3    32305098 2015-12-31 23:57:46 2016-01-01 07:43:00
4    32306529 2015-12-31 23:56:58 2016-01-01 03:24:00

            Complaint Type                    Descriptor    Location
Type  \
0  Noise - Street/Sidewalk              Loud Music/Party
Street/Sidewalk
1         Blocked Driveway                     No Access
Street/Sidewalk
2         Blocked Driveway                     No Access
Street/Sidewalk
3          Illegal Parking  Commercial Overnight Parking
Street/Sidewalk
4          Illegal Parking              Blocked Sidewalk
Street/Sidewalk

   Incident Zip       Incident Address       Street Name    Cross
```

```
Street 1  \
0       10034.0    71 VERMILYEA AVENUE  VERMILYEA AVENUE   ACADEMY
STREET
1       11105.0        27-07 23 AVENUE         23 AVENUE        27
STREET
2       10458.0  2897 VALENTINE AVENUE  VALENTINE AVENUE  EAST 198
STREET
3       10461.0    2940 BAISLEY AVENUE    BAISLEY AVENUE    EDISON
AVENUE
4       11373.0          87-14 57 ROAD           57 ROAD   SEABURY
STREET

   ... Resolution Action Updated Date Community Board    Borough  \
0  ...                  01-01-16 0:55    12 MANHATTAN  MANHATTAN
1  ...                  01-01-16 1:26       01 QUEENS     QUEENS
2  ...                  01-01-16 4:51        07 BRONX      BRONX
3  ...                  01-01-16 7:43        10 BRONX      BRONX
4  ...                  01-01-16 3:24       04 QUEENS     QUEENS

  X Coordinate (State Plane) Y Coordinate (State Plane) Park
Borough  \
0                  1005409.0                   254678.0    MANHATTAN

1                  1007766.0                   221986.0       QUEENS

2                  1015081.0                   256380.0        BRONX

3                  1031740.0                   243899.0        BRONX

4                  1019123.0                   206375.0       QUEENS


    Latitude  Longitude                                  Location  \
0  40.865682 -73.923501   (40.86568153633767, -73.92350095571744)
1  40.775945 -73.915094  (40.775945312321085, -73.91509393898605)
2  40.870325 -73.888525  (40.870324522111424, -73.88852464418646)
3  40.835994 -73.828379   (40.83599404683083, -73.82837939584206)
4  40.733060 -73.874170  (40.733059618956815, -73.87416975810375)

   Request_Closing_Time
0             55.250000
1             86.266667
2            291.516667
3            465.233333
4            207.033333

[5 rows x 26 columns]
```

Hypothesis Testing

```
p=sns.catplot(x='Complaint Type', y='Request_Closing_Time',
kind='box', data=df)
p.fig.set_figwidth(15)
p.fig.set_figheight(8)
plt.xticks(rotation=90)
plt.ylim((0,2000))
plt.show()
```



$H0$: 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

```
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()
```

```
   Request_Closing_Time                  Complaint
0             55.250000  Noise - Street/Sidewalk
1             86.266667         Blocked Driveway
2            291.516667         Blocked Driveway
3            465.233333          Illegal Parking
4            207.033333          Illegal Parking
```

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

	df	sum_sq	mean_sq	F	PR(>F)
Complaint	22.0	1.455049e+09	6.613860e+07	514.177089	0.0
Residual	298511.0	3.839747e+10	1.286300e+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

```
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)

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

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.