Customer_Service_Request_Code

August 10, 2022

1 Import Libraries/modules

[1]:
```
import pandas as pd
import numpy as np
import warnings
warnings.simplefilter("ignore")
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import style
%matplotlib inline
from scipy.stats import f_oneway
```

2 load the dataset in panda dataframe

[2]:
```
#import the 311_Service_Requests_from_2010_to_Present dataset CSV into the␣
↪panda dataframe#

csr_dataframe = pd.read_csv('311_Service_Requests_from_2010_to_Present.csv',␣
↪low_memory=False)
```

3 Task 1. Understand the dataset

3.0.1 1. Identify the shape of the dataset

[3]:
```
csr_dataframe.shape
```

[3]:
```
(364558, 53)
```

In the given dataset there are '364558' rows and '53' columns.

[4]:
```
#check column names
csr_dataframe.columns
```

[4]:
```
Index(['Unique Key', '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'],
      dtype='object')
```

[5]:
```
#check indexes
csr_dataframe.index
```

[5]:
```
RangeIndex(start=0, stop=364558, step=1)
```

[6]:
```
#Undrstand data set information
csr_dataframe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 364558 entries, 0 to 364557
Data columns (total 53 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   Unique Key                      364558 non-null  int64
 1   Created Date                    364558 non-null  object
 2   Closed Date                     362177 non-null  object
 3   Agency                          364558 non-null  object
 4   Agency Name                     364558 non-null  object
 5   Complaint Type                  364558 non-null  object
 6   Descriptor                      358057 non-null  object
 7   Location Type                   364425 non-null  object
 8   Incident Zip                    361560 non-null  float64
 9   Incident Address                312859 non-null  object
 10  Street Name                     312859 non-null  object
 11  Cross Street 1                  307370 non-null  object
 12  Cross Street 2                  306753 non-null  object
 13  Intersection Street 1           51120 non-null   object
 14  Intersection Street 2           50512 non-null   object
 15  Address Type                    361306 non-null  object
 16  City                            361561 non-null  object
 17  Landmark                        375 non-null     object
 18  Facility Type                   362169 non-null  object
 19  Status                          364558 non-null  object
 20  Due Date                        364555 non-null  object
 21  Resolution Description          364558 non-null  object
```

```
 22  Resolution Action Updated Date  362156 non-null  object
 23  Community Board                 364558 non-null  object
 24  Borough                         364558 non-null  object
 25  X Coordinate (State Plane)      360528 non-null  float64
 26  Y Coordinate (State Plane)      360528 non-null  float64
 27  Park Facility Name              364558 non-null  object
 28  Park Borough                    364558 non-null  object
 29  School Name                     364558 non-null  object
 30  School Number                   364558 non-null  object
 31  School Region                   364557 non-null  object
 32  School Code                     364557 non-null  object
 33  School Phone Number             364558 non-null  object
 34  School Address                  364558 non-null  object
 35  School City                     364558 non-null  object
 36  School State                    364558 non-null  object
 37  School Zip                      364557 non-null  object
 38  School Not Found                364558 non-null  object
 39  School or Citywide Complaint    0 non-null       float64
 40  Vehicle Type                    0 non-null       float64
 41  Taxi Company Borough            0 non-null       float64
 42  Taxi Pick Up Location           0 non-null       float64
 43  Bridge Highway Name             297 non-null     object
 44  Bridge Highway Direction        297 non-null     object
 45  Road Ramp                       262 non-null     object
 46  Bridge Highway Segment          262 non-null     object
 47  Garage Lot Name                 0 non-null       float64
 48  Ferry Direction                 1 non-null       object
 49  Ferry Terminal Name             2 non-null       object
 50  Latitude                        360528 non-null  float64
 51  Longitude                       360528 non-null  float64
 52  Location                        360528 non-null  object
dtypes: float64(10), int64(1), object(42)
memory usage: 147.4+ MB
```

[7]:
```
# understand sample data
csr_dataframe.head()
```

[7]:
```
   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]
```

3.0.2 2. Identify variables with null values

[8]:
```
# method 1 - solution

''' isnull function along with sum function can Find columns with Null values␣
↪and their respective count
```

```
here in output non 0 value denotes the no of null values a column is having'''

csr_dataframe.isnull().sum(axis = 0)
```

[8]:
```
Unique Key                              0
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
dtype: int64
```

[9]:
```
# method 2
#Below code can also be used to find only those columns columns which have null␣
↪values,

print("Below are the columns having null data : \n", csr_dataframe.
↪columns[csr_dataframe.isnull().any()].tolist())
print("\n total no of columns : ", len(csr_dataframe.columns))
print("total no of columns having null data : ", len(csr_dataframe.
↪columns[csr_dataframe.isnull().any()]))
print("total no of not null data columns :", len(csr_dataframe.
↪columns[csr_dataframe.notnull().all()]))
```

```
Below are the columns having null data :
 ['Closed Date', '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', 'Due Date', 'Resolution Action Updated Date', 'X Coordinate
(State Plane)', 'Y Coordinate (State Plane)', 'School Region', 'School Code',
'School Zip', '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']

 total no of columns :  53
total no of columns having null data :  35
total no of not null data columns : 18
```

- From above we can see that, there are total of 53 columns in the dataset
- out of which 35 has atleast 1 null record and 18 columns have no null records

4 Task 2. Perform basic data exploratory analysis:

For the EASE of analysis - Replace the special Characters in the Dataframe

[10]:
```
csr_dataframe.columns = csr_dataframe.columns.str.replace(" ","_")
```

[11]:
```
csr_dataframe.columns
```

[11]:
```
Index(['Unique_Key', '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'],
      dtype='object')
```

4.0.1 1. Utilize missing value treatment

- Below from point 'a' to 'e', Utilize missing value treatment is done:
  - a. Find and drop columns having all Null data
  - b. Find and drop columns having most (85%) of the NULL data
  - c. Some columns in the data aren't just useful for this project requirement and analysis, its best to drop these columns
  - d. Closed date, Latitude and Longitude have missing values, best to remove the rows where data in those columns are missing
  - e. Impute the NA value with Unknown City

a. Find and drop columns having all Null data

[12]:
```
#Find columns with all nul records
print("Below columns does not have any data/ (all rows are null) : \n \n",␣
 ↪csr_dataframe.columns[csr_dataframe.isnull().all()])

#remove above columns having all null records
csr_dataframe.dropna(axis= 1 , how='all', inplace=True)

#print the shape of the dataframe
print("\n After treatment shape of the dataframe is : \n",csr_dataframe.shape)
```

```
Below columns does not have any data/ (all rows are null) :

 Index(['School_or_Citywide_Complaint', 'Vehicle_Type', 'Taxi_Company_Borough',
       'Taxi_Pick_Up_Location', 'Garage_Lot_Name'],
      dtype='object')
```

```
After treatment shape of the dataframe is :
(364558, 48)
```

- There is no data for column 'School_or_Citywide_Complaint', 'Vehicle_Type', 'Taxi_Company_Borough', 'Taxi_Pick_Up_Location', 'Garage_Lot_Name'
- These columns are dropped.

b. Find and drop columns having most of the NULL data

[13]:
```
#taken 85% but this value is uaully discussed with business before removing of␣
↪the columns

#Find column having mostly the NULL data
most_Null_data = [i for i in csr_dataframe.columns if csr_dataframe[i].isnull().
↪sum() > 0.85*len(csr_dataframe)]

print("Column having mostly the NULL data :\n \n", most_Null_data)

#drop columns having mostly the NULL data
csr_dataframe.drop(columns = most_Null_data, inplace=True)


#print the shape of the dataframe
print("\n After treatment shape of the dataframe is : \n",csr_dataframe.shape)
```

```
Column having mostly the NULL data :

 ['Intersection_Street_1', 'Intersection_Street_2', 'Landmark',
'Bridge_Highway_Name', 'Bridge_Highway_Direction', 'Road_Ramp',
'Bridge_Highway_Segment', 'Ferry_Direction', 'Ferry_Terminal_Name']

 After treatment shape of the dataframe is :
 (364558, 39)
```

- most of the data is null for columns 'Intersection_Street_1', 'Intersection_Street_2', 'Landmark', 'Bridge_Highway_Name', 'Bridge_Highway_Direction', 'Road_Ramp', 'Bridge_Highway_Segment', 'Ferry_Direction', 'Ferry_Terminal_Name'
- these columns are dropped

c. some columns in the data aren't just useful to this analysis, its best to remove these columns

[14]:
```
# A list of columns to remove from the dataframe
```

```
unwanted_column_list = ['Agency_Name',  'Descriptor', 'Location_Type',␣
↪'Incident_Zip','Incident_Address', 'Street_Name', 'Cross_Street_1',␣
↪'Cross_Street_2','Address_Type', 'Facility_Type', 'Status', 'Due_Date',␣
↪'Resolution_Description',␣
↪'Resolution_Action_Updated_Date','Community_Board',␣
↪'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', 'Location']

#Drop columns of above list
csr_dataframe.drop(unwanted_column_list, inplace=True, axis=1)

#print the shape of the dataframe
print("\n After treatment shape of the dataframe is : \n",csr_dataframe.shape)
```

```
 After treatment shape of the dataframe is :
 (364558, 9)
```

[15]:
```
csr_dataframe.columns
```

[15]:
```
Index(['Unique_Key', 'Created_Date', 'Closed_Date', 'Agency', 'Complaint_Type',
       'City', 'Borough', 'Latitude', 'Longitude'],
      dtype='object')
```

d. Closed date, Latitude, and Longitude all have missing values, best to remove the rows where data in those columns are missing

[16]:
```
csr_dataframe = csr_dataframe[(csr_dataframe['Latitude'].notnull())&␣
↪(csr_dataframe['Longitude'].notnull()) & (csr_dataframe['Closed_Date'].
↪notnull())]

#print the shape of the dataframe
print("\n After treatment shape of the dataframe is : \n",csr_dataframe.shape)
```

```
 After treatment shape of the dataframe is :
 (360470, 9)
```

[17]:
```
csr_dataframe[['Closed_Date','Created_Date']].isnull().sum()
```

[17]:
```
Closed_Date     0
Created_Date    0
dtype: int64
```

e. Impute the NA value with Unknown City

- Since no of Nulls are more filling up Na cities with most frequest occurred city won't be good option

- It is better to impute the NA with Unknown city

[18]:
```
# impute the NA value with Unknown City
csr_dataframe['City'].fillna('Unknown City', inplace=True)

#print the shape of the dataframe
print("\n After treatment shape of the dataframe is : \n",csr_dataframe.shape)

csr_dataframe[['City', 'Complaint_Type']].isnull().sum()
```

```
 After treatment shape of the dataframe is :
 (360470, 9)
```

[18]:
```
City              0
Complaint_Type    0
dtype: int64
```

[19]:
```
csr_dataframe.isnull().sum(axis = 0)
```

[19]:
```
Unique_Key        0
Created_Date      0
Closed_Date       0
Agency            0
Complaint_Type    0
City              0
Borough           0
Latitude          0
Longitude         0
dtype: int64
```

4.0.2 2. Analyze the date column and remove the entries if it has an incorrect timeline

```
* Created Date, Closed Date,Resolution Action Updated Date, Due Date are the Date columns

    * 1. Created Date : No Null data
    * 2. Closed Date : row having null data is already removed in above steps
    * 3. Resolution Action Updated Date : column is irrelevant hence already remove in above s
    * 2. Due Date are the Date columns  : column is irrelevant hence already remove in above s
```

- Column 'Created Date' and 'Closed Date' will to be converted into datetime datatype
- For column 'Created Date' and 'Closed Date' rows having null data will be removed.
- New column 'Request_Closing_Time' will be created which will be the difference of 'Closed Date' and 'Created Date'.

[20]:
```
#correct the datatype of Date columns


#Datatype of Date columns
```

```
print("Datatype of Date columns before treatment : \n",␣
↪csr_dataframe[['Created_Date','Closed_Date']].dtypes)

#First convert the Date columns which are of object type into the Date format
csr_dataframe['Created_Date'] = pd.
↪to_datetime(csr_dataframe['Created_Date'],format='%m/%d/%Y %I:%M:%S %p' ,␣
↪errors='coerce',infer_datetime_format=True)
csr_dataframe['Closed_Date'] = pd.
↪to_datetime(csr_dataframe['Closed_Date'],format='%m/%d/%Y %I:%M:%S %p' ,␣
↪errors='coerce',infer_datetime_format=True)

print("\n Datatype of Date columns After treatment : \n",␣
↪csr_dataframe[['Created_Date','Closed_Date']].dtypes)
```

```
Datatype of Date columns before treatment :
 Created_Date    object
Closed_Date     object
dtype: object

 Datatype of Date columns After treatment :
 Created_Date    datetime64[ns]
Closed_Date     datetime64[ns]
dtype: object
```

[21]:

```
#Find response time

csr_dataframe['Request_Closing_Time'] = (csr_dataframe['Closed_Date'].values -␣
↪csr_dataframe['Created_Date'].values)
csr_dataframe['Request_Closing_Time_mins'] =␣
↪csr_dataframe['Request_Closing_Time']/np.timedelta64(1,'m')
```

[22]:

```
# Get the statistical information

csr_dataframe['Request_Closing_Time_mins'].describe()
```

[22]:

```
count    360470.000000
mean        251.344535
std         349.555692
min           1.016667
25%          75.483333
50%         160.066667
75%         314.029167
max       35572.366667
Name: Request_Closing_Time_mins, dtype: float64
```

4.0.3 Outlier identification and verification/removal of Date data which is not in timeline is done in last section of this notebook . Please refer last section

4.0.4 3. Draw a frequency plot for city-wise complaints

- First create a dataset having cities and respective count of complaints (basically group by city)
- Then draw a frequency plot for city-wise complaints (This will be hitogram plot)

[23]:
```
#Check the count of complaints city wise
a = pd.DataFrame({'Count of complaints Citywise' : csr_dataframe.
 ↪groupby('City')['Complaint_Type'].size()})
a.sort_values( by = 'Count of complaints Citywise', ascending = False)
```

[23]:
```
                     Count of complaints Citywise
City
BROOKLYN                                   118632
NEW YORK                                    76634
BRONX                                       49048
STATEN ISLAND                               15326
JAMAICA                                      8920
ASTORIA                                      7974
FLUSHING                                     7481
RIDGEWOOD                                    6388
CORONA                                       5382
WOODSIDE                                     4354
EAST ELMHURST                                3557
OZONE PARK                                   3446
ELMHURST                                     3438
SOUTH RICHMOND HILL                          3430
MASPETH                                      3116
WOODHAVEN                                    3102
LONG ISLAND CITY                             3019
SOUTH OZONE PARK                             2668
FRESH MEADOWS                                2449
RICHMOND HILL                                2333
MIDDLE VILLAGE                               2290
QUEENS VILLAGE                               2251
FOREST HILLS                                 2120
JACKSON HEIGHTS                              2105
REGO PARK                                    1805
BAYSIDE                                      1548
COLLEGE POINT                                1544
FAR ROCKAWAY                                 1396
WHITESTONE                                   1367
HOLLIS                                       1231
HOWARD BEACH                                 1143
SPRINGFIELD GARDENS                          1094
```

```
ROSEDALE                                      1086
SAINT ALBANS                                  1047
KEW GARDENS                                   1008
SUNNYSIDE                                      944
Astoria                                        905
ROCKAWAY PARK                                  829
OAKLAND GARDENS                                715
LITTLE NECK                                    712
CAMBRIA HEIGHTS                                617
BELLEROSE                                      487
GLEN OAKS                                      361
ARVERNE                                        258
FLORAL PARK                                    196
Long Island City                               170
Woodside                                       166
NEW HYDE PARK                                  129
CENTRAL PARK                                   110
Unknown City                                    41
QUEENS                                          36
BREEZY POINT                                    31
East Elmhurst                                   30
Howard Beach                                     1
```

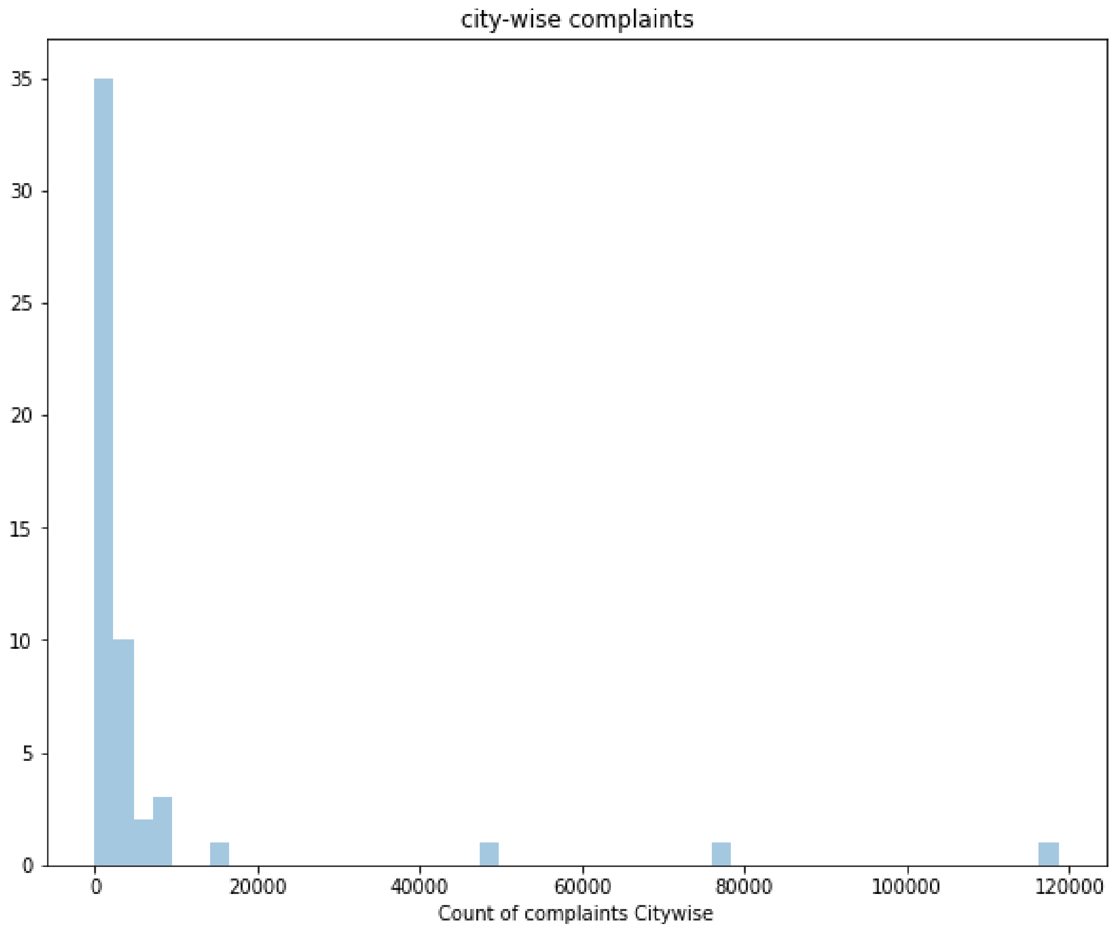
[24]:
```python
csr_dataframe.reset_index(drop=True)
```

[24]:
```
        Unique_Key        Created_Date         Closed_Date Agency  \
0         32310363 2015-12-31 23:59:45 2016-01-01 00:55:15   NYPD
1         32309934 2015-12-31 23:59:44 2016-01-01 01:26:57   NYPD
2         32309159 2015-12-31 23:59:29 2016-01-01 04:51:03   NYPD
3         32305098 2015-12-31 23:57:46 2016-01-01 07:43:13   NYPD
4         32306529 2015-12-31 23:56:58 2016-01-01 03:24:42   NYPD
…              …                 …                   …    …
360465    29609918 2015-01-01 00:04:44 2015-01-01 10:22:31   NYPD
360466    29608392 2015-01-01 00:04:28 2015-01-01 02:25:02   NYPD
360467    29607589 2015-01-01 00:01:30 2015-01-01 00:20:33   NYPD
360468    29610889 2015-01-01 00:01:29 2015-01-01 02:42:22   NYPD
360469    29611816 2015-01-01 00:00:50 2015-01-01 02:47:50   NYPD

                 Complaint_Type           City    Borough   Latitude  \
0       Noise - Street/Sidewalk       NEW YORK  MANHATTAN  40.865682
1              Blocked Driveway        ASTORIA     QUEENS  40.775945
2              Blocked Driveway          BRONX      BRONX  40.870325
3               Illegal Parking          BRONX      BRONX  40.835994
4               Illegal Parking       ELMHURST     QUEENS  40.733060
…                             …              …         …          …
360465          Illegal Parking      WOODHAVEN     QUEENS  40.695145
360466          Noise - Vehicle          BRONX      BRONX  40.867830
```

```
360467  Noise - Street/Sidewalk         NEW YORK  MANHATTAN  40.821647
360468         Blocked Driveway            BRONX      BRONX  40.886361
360469         Blocked Driveway  SOUTH OZONE PARK     QUEENS  40.674212

        Longitude Request_Closing_Time  Request_Closing_Time_mins
0      -73.923501      0 days 00:55:30                  55.500000
1      -73.915094      0 days 01:27:13                  87.216667
2      -73.888525      0 days 04:51:34                 291.566667
3      -73.828379      0 days 07:45:27                 465.450000
4      -73.874170      0 days 03:27:44                 207.733333
…             …                  …                          …
360465 -73.860949      0 days 10:17:47                 617.783333
360466 -73.907178      0 days 02:20:34                 140.566667
360467 -73.950873      0 days 00:19:03                  19.050000
360468 -73.853290      0 days 02:40:53                 160.883333
360469 -73.803585      0 days 02:47:00                 167.000000

[360470 rows x 11 columns]
```

Visualize

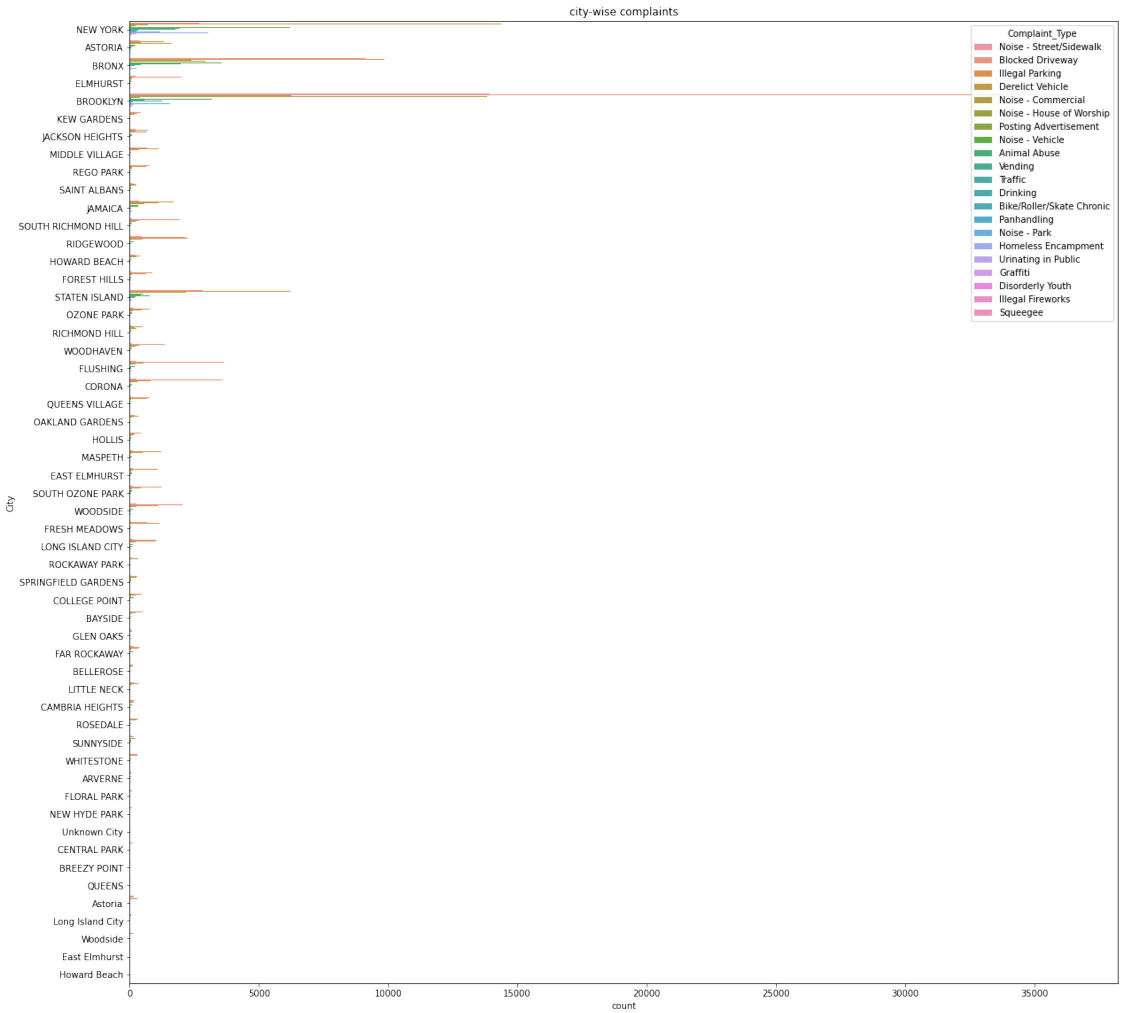
[25]:
```
# Visualization of frequency plot for city-wise complaints - solution 1

plt.figure(figsize=(10,8))

sns.distplot(a['Count of complaints Citywise'], kde=False)
plt.xlabel("Count of complaints Citywise")
plt.title('city-wise complaints')
plt.show()
```



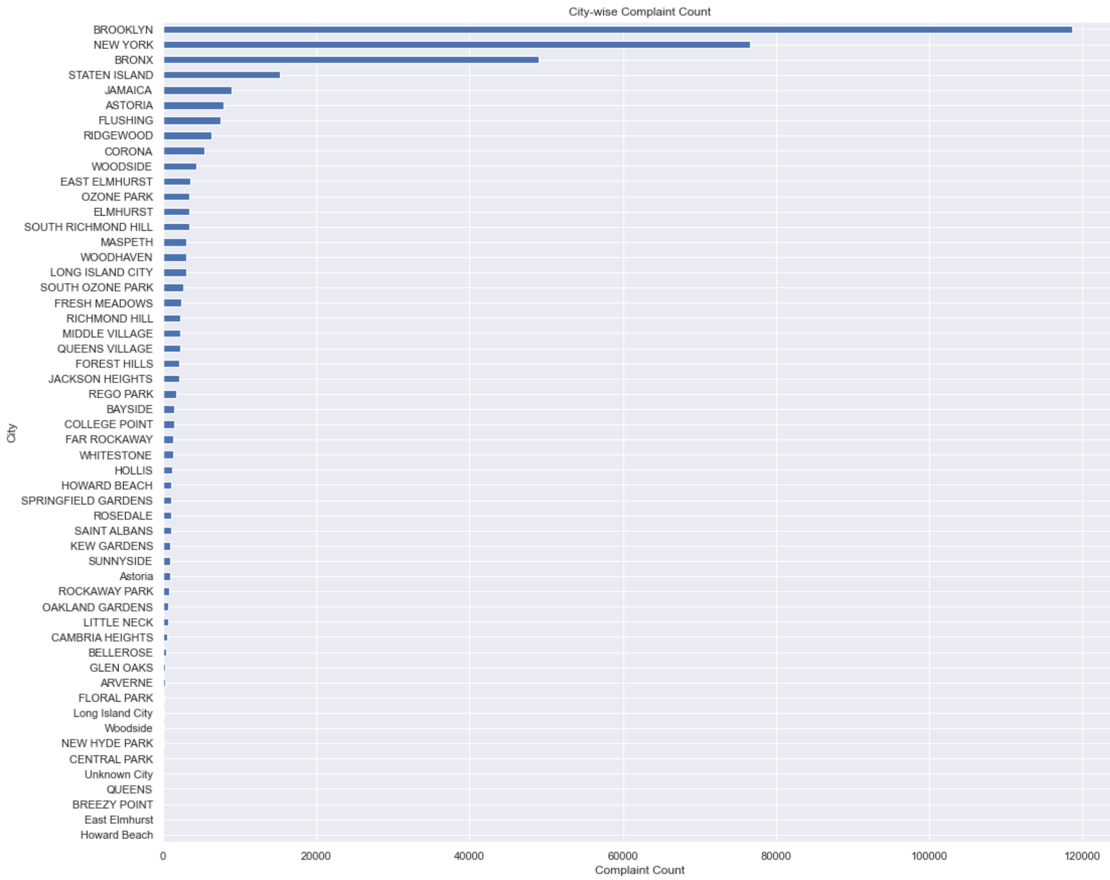
- Here frequency plot using distplot is not very useful
- countplot show the counts of observations in each categorical bin using bars. A count plot can be thought of as a histogram across a categorical, instead of quantitative, variable.
- hence below countplot can be used to visualize the frequency distribution of city-wise complaints

[26]:
```
# Visualization of frequency plot for city-wise complaints - solution 2

plt.figure(figsize=(20,20))
plt.title('city-wise complaints')
sns.countplot(y="City",data=csr_dataframe,hue = 'Complaint_Type')
```

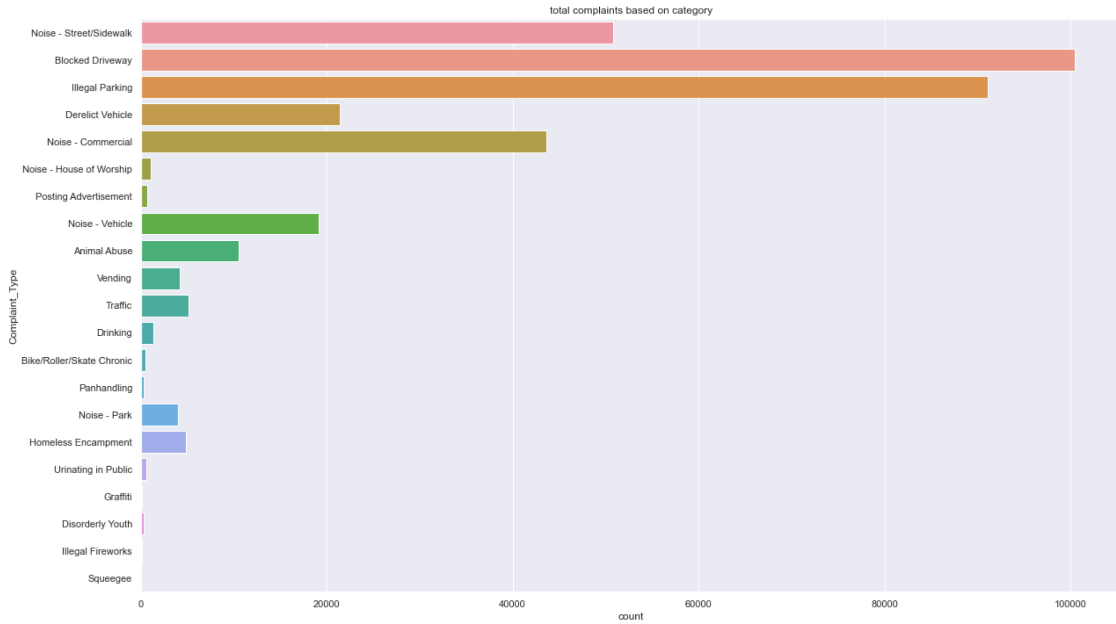
[26]:
```
<AxesSubplot:title={'center':'city-wise complaints'}, xlabel='count',
ylabel='City'>
```



[27]:
```python
#city-wise complaints (base on city)

sns.set()
csr_dataframe['City'].value_counts().sort_values(ascending= True).plot(kind=
    'barh', figsize=(17,15), title="City-wise Complaint Count")
plt.xlabel('Complaint Count')
plt.ylabel('City')
plt.show()
```



[28]:
```python
#total complaints based on category

plt.figure(figsize=(20,12))
plt.title('total complaints based on category')
sns.countplot(y= "Complaint_Type",data=csr_dataframe)
plt.show()
```



Conclusion - Above graphs shows that:

```
* 1. City 'BROOKLYN' has highest complaint types
* 2. maximum complaints exists for complaint type 'Blocked Driveway'
```

4.0.5 4. Draw scatter and hexbin plots for complaint concentration across Brooklyn

Notes- Based on the domain knowledge

- In dataset Brooklyn is present in both City and Borough
- but since 1898 Brooklyn is not considered as a City but as a Borough - Refer - https://en.wikipedia.org/wiki/Brooklyn
- hence the scatter and hexbin plots should be based on the Borough column not on the City column, Brooklyn is a borough not a city

[29]:
```python
#First make a dataset:
df_Brooklyn_Borough = csr_dataframe[csr_dataframe['Borough']=='BROOKLYN']
df_Brooklyn_Borough.head()
```

[29]:
```
    Unique_Key        Created_Date         Closed_Date Agency  \
5     32306554 2015-12-31 23:56:30 2016-01-01 01:50:11   NYPD
9     32308391 2015-12-31 23:53:58 2016-01-01 01:17:40   NYPD
13    32305074 2015-12-31 23:47:58 2016-01-01 08:18:47   NYPD
17    32310273 2015-12-31 23:44:52 2016-01-01 00:36:10   NYPD
18    32306617 2015-12-31 23:40:59 2016-01-01 02:37:28   NYPD

       Complaint_Type      City   Borough   Latitude  Longitude  \
5     Illegal Parking  BROOKLYN  BROOKLYN  40.660823 -73.992568
```

```
9     Blocked Driveway  BROOKLYN  BROOKLYN  40.623793 -73.999539
13     Illegal Parking  BROOKLYN  BROOKLYN  40.687511 -73.874505
17  Noise - Commercial  BROOKLYN  BROOKLYN  40.679154 -73.983430
18  Noise - Commercial  BROOKLYN  BROOKLYN  40.616550 -73.930202

   Request_Closing_Time  Request_Closing_Time_mins
5       0 days 01:53:41                 113.683333
9       0 days 01:23:42                  83.700000
13      0 days 08:30:49                 510.816667
17      0 days 00:51:18                  51.300000
18      0 days 02:56:29                 176.483333
```

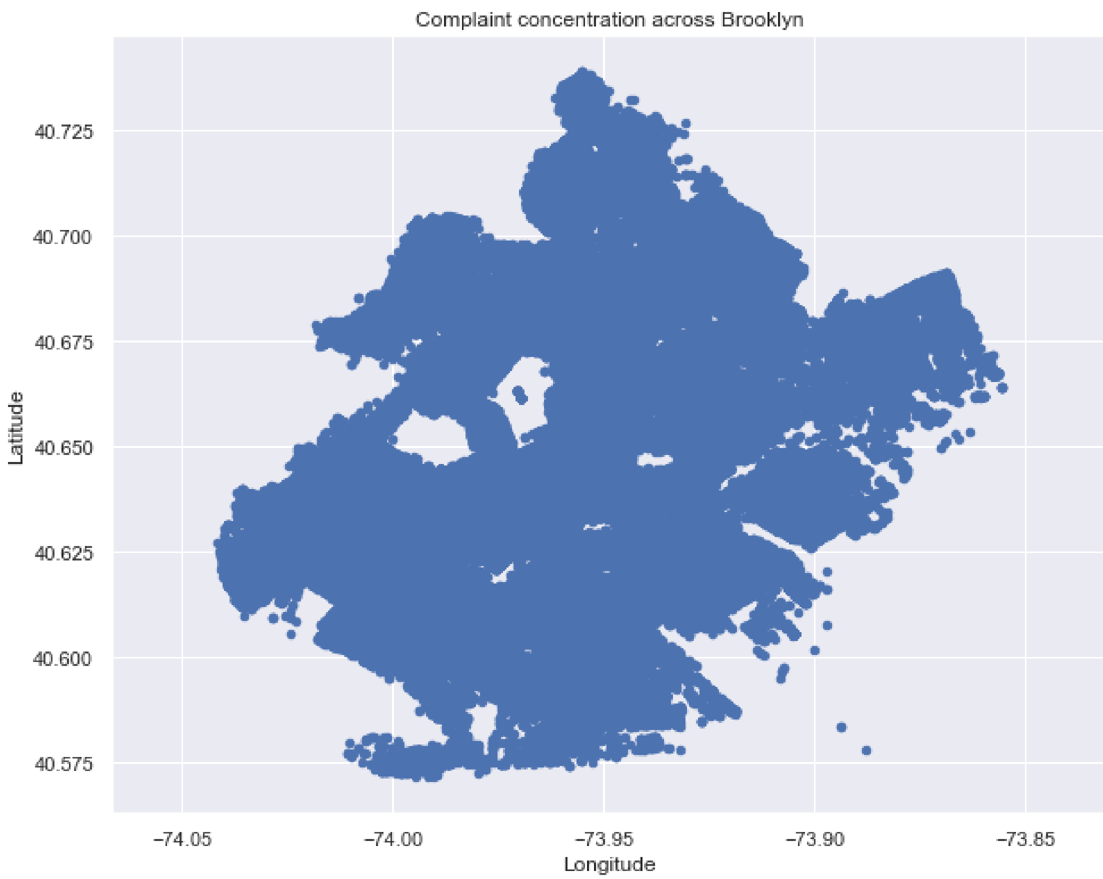
[30]:
```
df_Brooklyn_Borough['Complaint_Type'].value_counts()
```

[30]:
```
Blocked Driveway             36431
Illegal Parking              33461
Noise - Street/Sidewalk      13943
Noise - Commercial           13848
Derelict Vehicle              6246
Noise - Vehicle               5933
Animal Abuse                  3186
Noise - Park                  1558
Traffic                       1255
Homeless Encampment            939
Vending                        575
Noise - House of Worship       387
Drinking                       291
Urinating in Public            155
Bike/Roller/Skate Chronic      121
Disorderly Youth                79
Graffiti                        60
Illegal Fireworks               60
Posting Advertisement           58
Panhandling                     48
Name: Complaint_Type, dtype: int64
```

[31]:
```
#Complaint concentration across Brooklyn

#1. Using Scatter plot

df_Brooklyn_Borough[['Longitude', 'Latitude']].plot(kind='scatter',
    x='Longitude', y='Latitude', figsize=(10,8),title = 'Complaint␣
 ↪concentration across Brooklyn').axis('equal')
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be
```

```
avoided as value-mapping will have precedence in case its length matches with
*x* & *y*.  Please use the *color* keyword-argument or provide a 2D array with a
single row if you intend to specify the same RGB or RGBA value for all points.
```

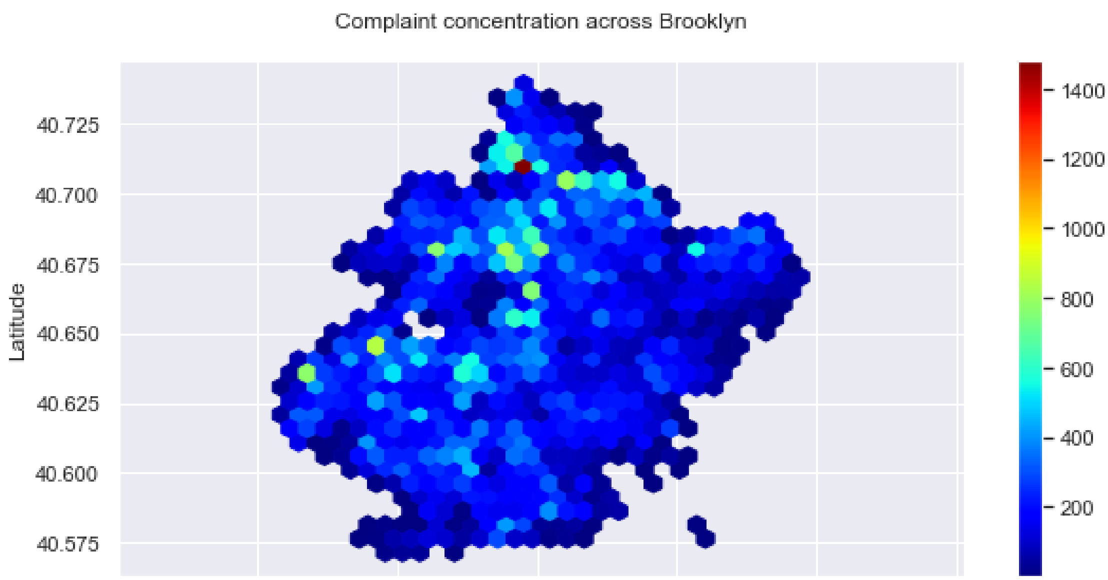


observation -

- Here Scatter plot is not providing much inights and it is inconclusive
- hexbin will be better indicator.

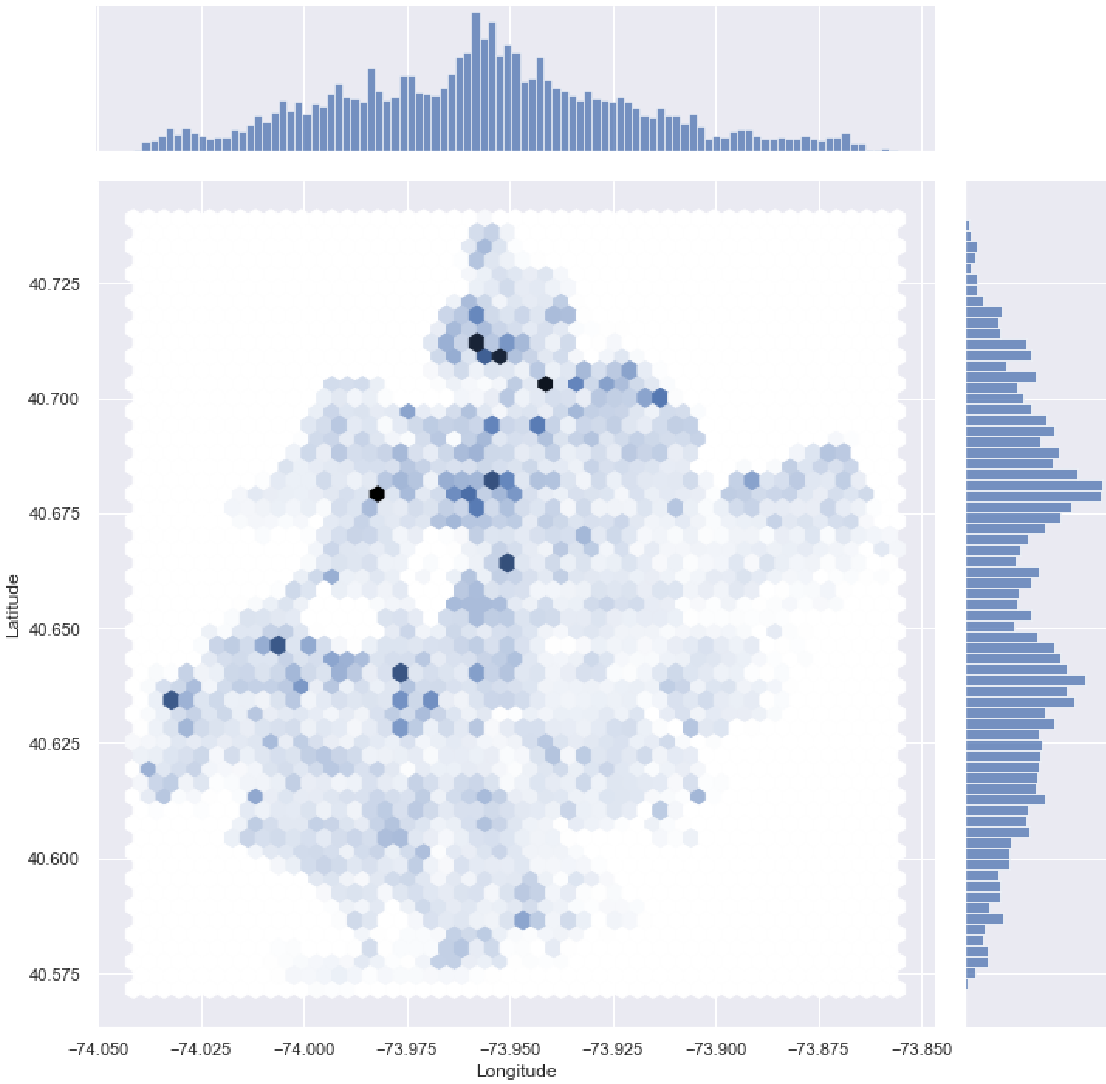
[32]:
```
#2. Using hexbins - Used both 'matplot' as well as 'seaborn' method

df_Brooklyn_Borough.plot(kind='hexbin', x='Longitude', y='Latitude',␣
 ↪gridsize=30,
   colormap = 'jet',mincnt=1,title = 'Complaint concentration across␣
 ↪Brooklyn\n', figsize=(10,5)).axis('equal')
```

[32]:
```
(-74.05061403048781, -73.8464793432815, 40.563150823850876, 40.74729501421672)
```



[33]:
```
sns.jointplot(data =df_Brooklyn_Borough ,  x='Longitude', y='Latitude',  kind =
    'hex',height=10)
```

[33]: <seaborn.axisgrid.JointGrid at 0x1b38b3d6f20>



Conclusion -

- Complaints are scattered all over the Brooklyn Borough in the range of latitude and longitude of (-74.05061403048781, -73.8464793432815, 40.563150823850876, 40.74729501421672)

5 Task 3. Find major types of complaints

Major types of complaints on the cleaned data

[34]:
```
major_complaints = csr_dataframe['Complaint_Type']

print("unique major complaints : \n \n", major_complaints.unique())
print("\n No of unique major complaints : \n", major_complaints.nunique())
```

```
unique major complaints :
```

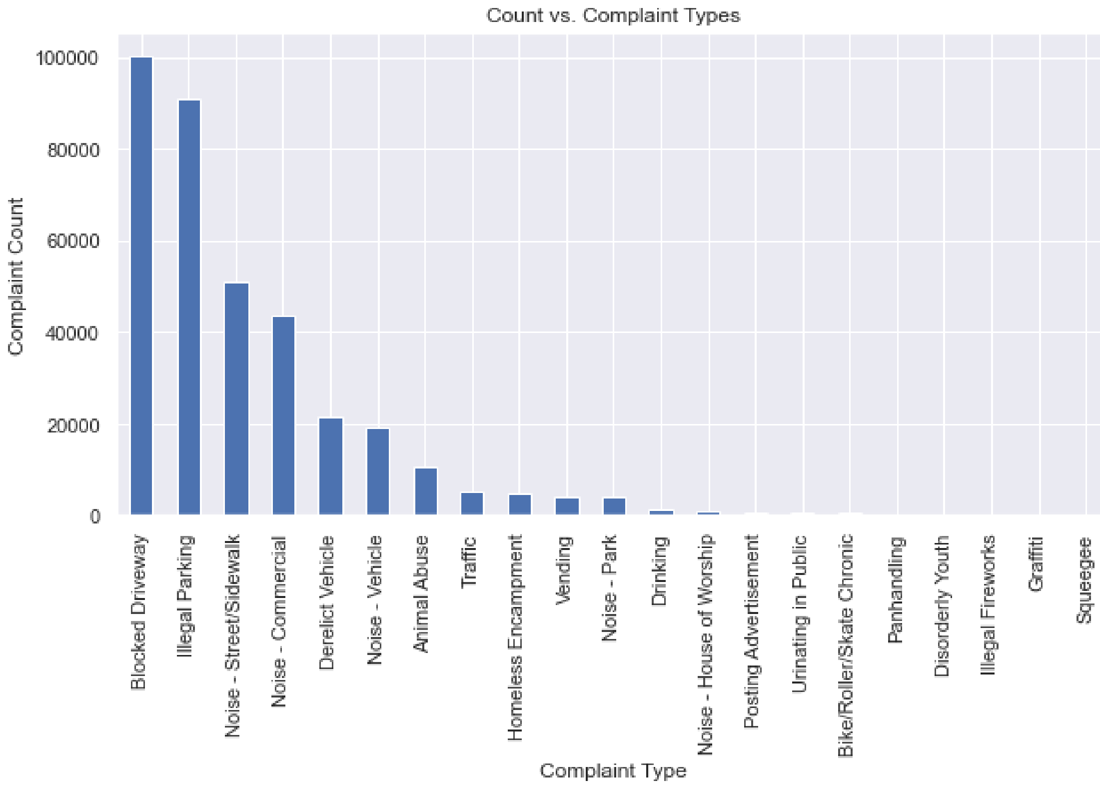
```
['Noise - Street/Sidewalk' 'Blocked Driveway' 'Illegal Parking'
'Derelict Vehicle' 'Noise - Commercial' 'Noise - House of Worship'
'Posting Advertisement' 'Noise - Vehicle' 'Animal Abuse' 'Vending'
'Traffic' 'Drinking' 'Bike/Roller/Skate Chronic' 'Panhandling'
'Noise - Park' 'Homeless Encampment' 'Urinating in Public' 'Graffiti'
'Disorderly Youth' 'Illegal Fireworks' 'Squeegee']

No of unique major complaints :
21
```

[35]:
```
major_complaints.value_counts()
```

[35]:
```
Blocked Driveway             100493
Illegal Parking               91095
Noise - Street/Sidewalk       50823
Noise - Commercial            43640
Derelict Vehicle              21427
Noise - Vehicle               19125
Animal Abuse                  10503
Traffic                        5169
Homeless Encampment            4830
Vending                        4164
Noise - Park                   3995
Drinking                       1400
Noise - House of Worship       1061
Posting Advertisement           679
Urinating in Public             641
Bike/Roller/Skate Chronic       463
Panhandling                     320
Disorderly Youth                314
Illegal Fireworks               167
Graffiti                        157
Squeegee                          4
Name: Complaint_Type, dtype: int64
```

5.0.1 1. Plot a bar graph of count vs. complaint types

[36]:
```
x=major_complaints.value_counts()
plt.figure(figsize=(10,5))
x.plot(kind = 'bar' , title = "Count vs. Complaint Types" , xlabel = 'Complaint␣
↪Type' , ylabel ='Complaint Count')
plt.show()
```



Conclusion -

- Maximum number of complainsts are occurring for complaint type = 'Blocked Driveway'

Lets Check the frequency of various types of complaints for New York city and Brooklyn

[37]:
```
csr_dataframe.loc[csr_dataframe['City']== 'NEW YORK']['Complaint_Type'].
 ↪value_counts()
```

[37]:
```
Noise - Street/Sidewalk      22081
Noise - Commercial           18668
Illegal Parking              14368
Noise - Vehicle               6179
Homeless Encampment           3021
Blocked Driveway              2687
Vending                       2620
Animal Abuse                  1926
Traffic                       1751
Noise - Park                  1200
Derelict Vehicle               688
Drinking                       320
Urinating in Public            264
```

```
Bike/Roller/Skate Chronic      249
Noise - House of Worship       217
Panhandling                    203
Disorderly Youth                80
Posting Advertisement           49
Illegal Fireworks               34
Graffiti                        25
Squeegee                         4
Name: Complaint_Type, dtype: int64
```

[38]:
```
csr_dataframe.loc[csr_dataframe['City']== 'BROOKLYN']['Complaint_Type'].
↪value_counts()
```

[38]:
```
Blocked Driveway             36431
Illegal Parking              33461
Noise - Street/Sidewalk      13944
Noise - Commercial           13848
Derelict Vehicle              6245
Noise - Vehicle               5933
Animal Abuse                  3186
Noise - Park                  1558
Traffic                       1253
Homeless Encampment            939
Vending                        575
Noise - House of Worship       387
Drinking                       291
Urinating in Public            155
Bike/Roller/Skate Chronic      121
Disorderly Youth                79
Graffiti                        60
Illegal Fireworks               60
Posting Advertisement           58
Panhandling                     48
Name: Complaint_Type, dtype: int64
```

5.0.2 2. Find the top 10 complaint types

[39]:
```
major_complaints.value_counts().nlargest(10).index
```

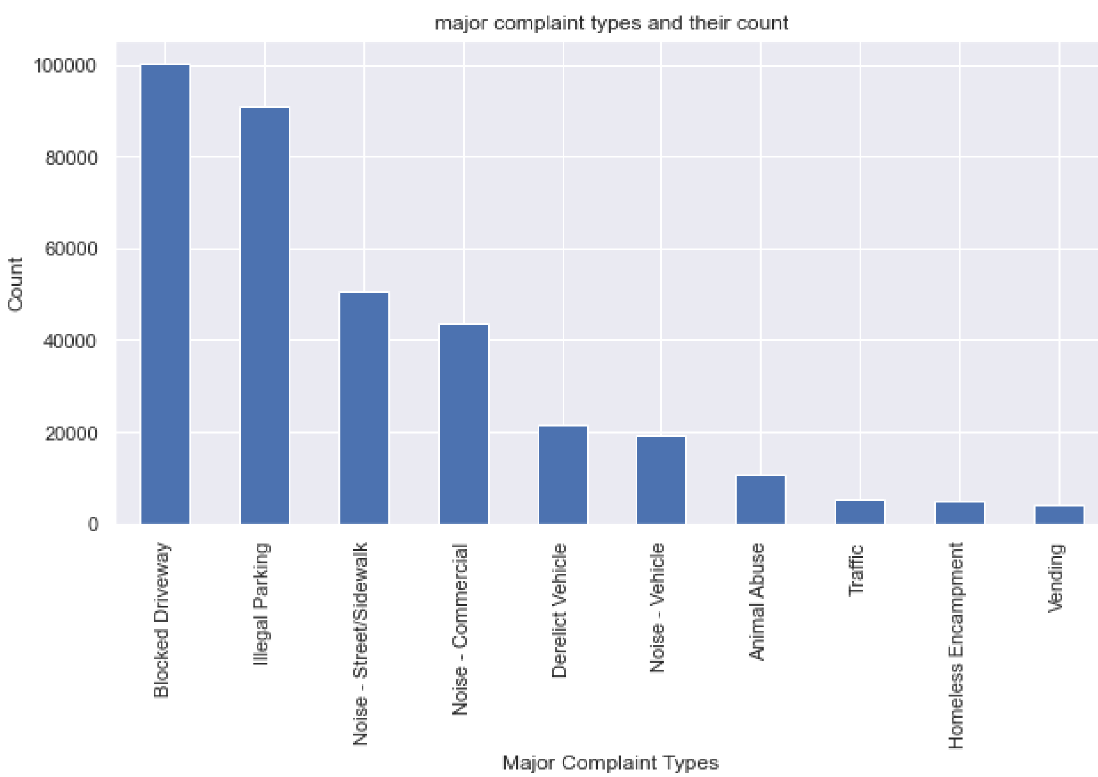
[39]:
```
Index(['Blocked Driveway', 'Illegal Parking', 'Noise - Street/Sidewalk',
       'Noise - Commercial', 'Derelict Vehicle', 'Noise - Vehicle',
       'Animal Abuse', 'Traffic', 'Homeless Encampment', 'Vending'],
      dtype='object')
```

[40]:
```
major_complaints.value_counts().nlargest(10)
```

[40]:
```
Blocked Driveway          100493
Illegal Parking            91095
Noise - Street/Sidewalk    50823
Noise - Commercial         43640
Derelict Vehicle           21427
Noise - Vehicle            19125
Animal Abuse               10503
Traffic                     5169
Homeless Encampment         4830
Vending                     4164
Name: Complaint_Type, dtype: int64
```

Display the major complaint types and their count

[41]:
```
y=major_complaints.value_counts().nlargest(10)
plt.figure(figsize=(10,5))
y.plot(kind = 'bar' , title = "major complaint types and their count" , xlabel␣
 ↪= 'Major Complaint Types' , ylabel ='Count')
plt.show()
```



5.0.3 3. Display the types of complaints in each city in a separate dataset

[42]:
```
city_complaint_dataset = pd.DataFrame({"Count": csr_dataframe.
 ↪groupby(["City","Complaint_Type"]).size()}).reset_index()
city_complaint_dataset.sort_values("Count", ascending = False)
```

[42]:
```
             City              Complaint_Type  Count
105      BROOKLYN            Blocked Driveway  36431
112      BROOKLYN             Illegal Parking  33461
468      NEW YORK   Noise - Street/Sidewalk   22081
465      NEW YORK          Noise - Commercial  18668
85          BRONX            Blocked Driveway  17052
..            …                           …      …
382   KEW GARDENS                     Vending      1
515        QUEENS  Noise - House of Worship      1
551     REGO PARK        Urinating in Public      1
164        CORONA                 Panhandling      1
584     RIDGEWOOD       Posting Advertisement      1

[782 rows x 3 columns]
```

6 Task 4. Visualize the major types of complaints in each city

- First create the Dataframe
- Next create the stacked bar chart
- stacked bar chart shows the types of complaints in each city in a single chart, where diffrent colors show the different types of complaints

[43]:
```
# create a list of major Complaint Types

major_complaint_list=major_complaints.value_counts().nlargest(10).index.
 ↪to_list()
major_complaint_list
```

[43]:
```
['Blocked Driveway',
 'Illegal Parking',
 'Noise - Street/Sidewalk',
 'Noise - Commercial',
 'Derelict Vehicle',
 'Noise - Vehicle',
 'Animal Abuse',
 'Traffic',
 'Homeless Encampment',
 'Vending']
```

[44]:
```
# Create a Dataset where for only 'major type of complaints' and corresponding␣
 ↪City name
```

```
city_major_complaint_dataset = pd.DataFrame()
for ct in major_complaint_list:
    ␣
  ↪city_major_complaint_dataset[ct]=csr_dataframe[csr_dataframe['Complaint_Type']==ct]['City']
  ↪value_counts()

#city_major_complaint_dataset = csr_dataframe.groupby(['City','Complaint␣
  ↪Type']).size().unstack()
#city_major_complaint_dataset =␣
  ↪city_major_complaint_dataset[major_complaint_list]

city_major_complaint_dataset.head()
```

[44]:

```
           Blocked Driveway  Illegal Parking  Noise - Street/Sidewalk  \
BROOKLYN              36431          33461.0                  13944.0
BRONX                 17052           9857.0                   9118.0
FLUSHING               3640           2248.0                    241.0
JAMAICA                3619           1696.0                    359.0
CORONA                 3597            791.0                    242.0

           Noise - Commercial  Derelict Vehicle  Noise - Vehicle  Animal Abuse  \
BROOKLYN              13848.0            6245.0           5933.0        3186.0
BRONX                  2941.0            2399.0           3545.0        1967.0
FLUSHING                220.0             531.0            147.0         191.0
JAMAICA                 552.0            1132.0            336.0         317.0
CORONA                  281.0              72.0            110.0         104.0

           Traffic  Homeless Encampment  Vending
BROOKLYN    1253.0                939.0    575.0
BRONX        426.0                274.0    431.0
FLUSHING      59.0                 26.0     37.0
JAMAICA      632.0                 93.0     24.0
CORONA        14.0                 26.0     65.0
```

[45]:

```
city_major_complaint_dataset.columns
```

[45]:

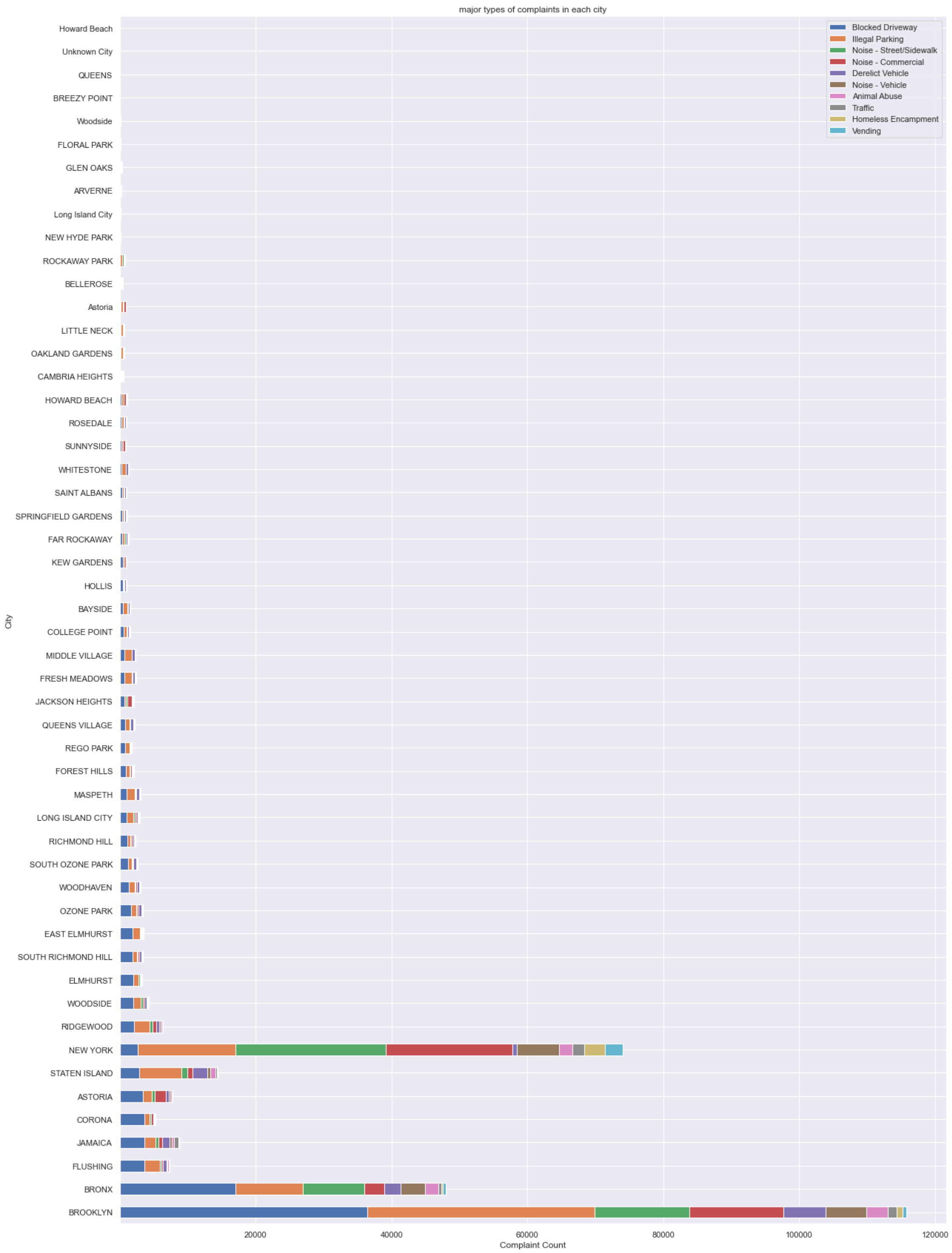
```
Index(['Blocked Driveway', 'Illegal Parking', 'Noise - Street/Sidewalk',
       'Noise - Commercial', 'Derelict Vehicle', 'Noise - Vehicle',
       'Animal Abuse', 'Traffic', 'Homeless Encampment', 'Vending'],
      dtype='object')
```

Visualize - Display the major types of complaints in each city

[46]:

```
city_major_complaint_dataset.plot(kind = 'barh' , figsize=(20,30),␣
  ↪stacked=True, title = "major types of complaints in each city" , xlabel =␣
  ↪'City' , ylabel ='Count')
plt.xlabel('Complaint Count')
```

```
plt.ylabel('City')
plt.show()
```



Conclusion :

- Above graph shows that the complaint Type = 'Blocked Driveway' is occurring maximum no of times in most of the Cities followded by 'Illegal Parking'

7 Task 5. Check if the average response time across various types of complaints

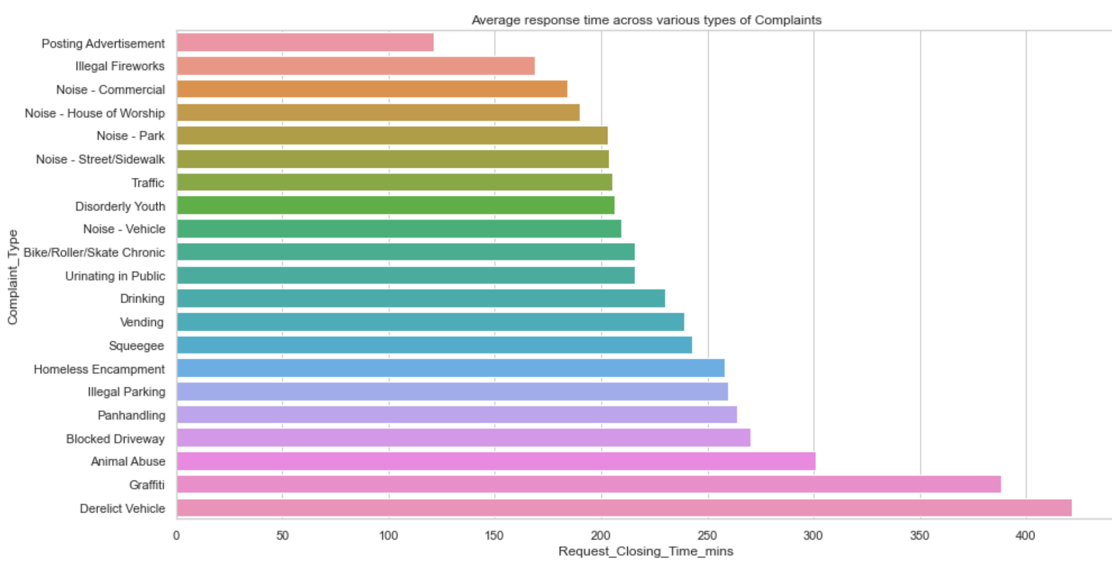
[47]:
```
# Create a dataset of average response time for each type of complaint

response_timeDataset = ␣
↪csr_dataframe[['Complaint_Type','Request_Closing_Time_mins']]
avg_response_time = response_timeDataset.groupby(['Complaint_Type'] , dropna =␣
↪False)['Request_Closing_Time_mins'].mean().fillna(0).to_frame()
avg_response_time['Complaint_Type']=avg_response_time.index
avg_response_time
```

[47]:
```
                           Request_Closing_Time_mins  \
Complaint_Type
Animal Abuse                              300.851849
Bike/Roller/Skate Chronic                 215.699928
Blocked Driveway                          270.295141
Derelict Vehicle                          421.339650
Disorderly Youth                          206.595913
Drinking                                  230.066417
Graffiti                                  387.939066
Homeless Encampment                       257.912484
Illegal Fireworks                         168.705788
Illegal Parking                           259.734646
Noise - Commercial                        184.014285
Noise - House of Worship                  189.970295
Noise - Park                              203.375899
Noise - Street/Sidewalk                   203.627450
Noise - Vehicle                           209.773496
Panhandling                               263.713385
Posting Advertisement                     121.437604
Squeegee                                  242.670833
Traffic                                   205.375314
Urinating in Public                       215.988222
Vending                                   239.239177

                                      Complaint_Type
Complaint_Type
Animal Abuse                            Animal Abuse
Bike/Roller/Skate Chronic  Bike/Roller/Skate Chronic
Blocked Driveway                    Blocked Driveway
Derelict Vehicle                    Derelict Vehicle
```

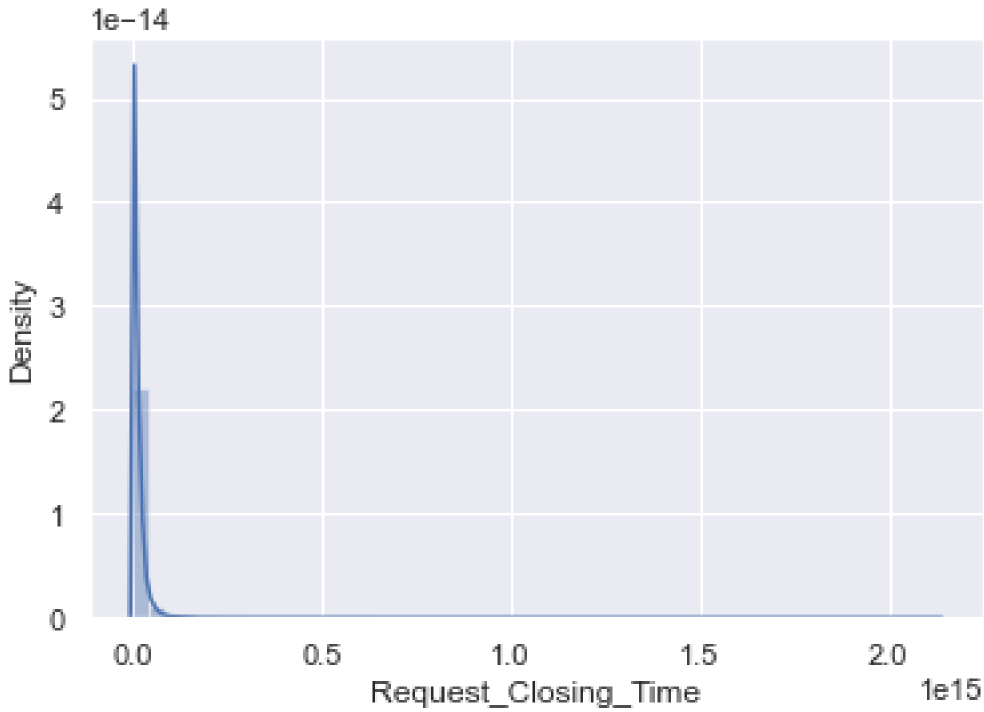
```
Disorderly Youth                    Disorderly Youth
Drinking                                    Drinking
Graffiti                                    Graffiti
Homeless Encampment              Homeless Encampment
Illegal Fireworks                  Illegal Fireworks
Illegal Parking                      Illegal Parking
Noise - Commercial                Noise - Commercial
Noise - House of Worship    Noise - House of Worship
Noise - Park                            Noise - Park
Noise - Street/Sidewalk      Noise - Street/Sidewalk
Noise - Vehicle                      Noise - Vehicle
Panhandling                              Panhandling
Posting Advertisement          Posting Advertisement
Squeegee                                    Squeegee
Traffic                                      Traffic
Urinating in Public              Urinating in Public
Vending                                      Vending
```

[48]:
```python
# Draw the average response time across various types of complaints

sns.set_theme(style="whitegrid")
plt.figure(figsize = (15,8))
sns.barplot(y="Complaint_Type", x="Request_Closing_Time_mins", 
 ↪data=avg_response_time.sort_values('Request_Closing_Time_mins'))
plt.title("Average response time across various types of Complaints")
```

[48]: Text(0.5, 1.0, 'Average response time across various types of Complaints')



[49]:
```
sns.set()
sns.distplot(csr_dataframe.Request_Closing_Time, hist= True)
plt.show()
```



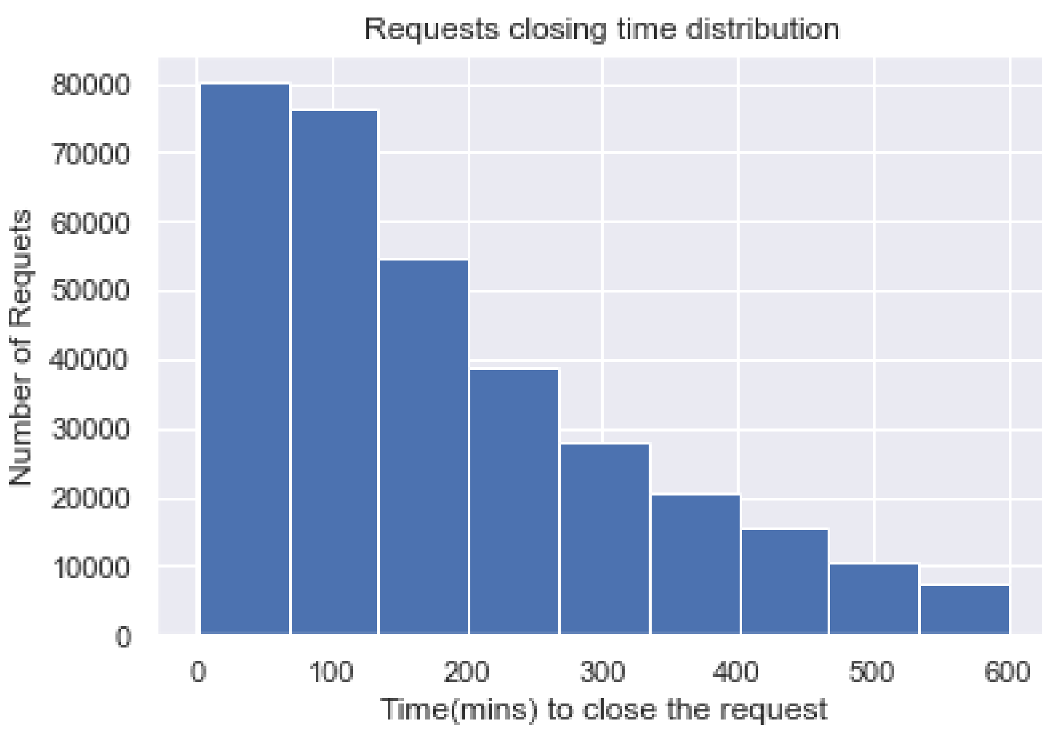
[50]:
```
# Viewing the descriptive statistics on the Processing Time can give some␣
↪insights on turn around time


mean = response_timeDataset['Request_Closing_Time_mins'].mean()
std = response_timeDataset['Request_Closing_Time_mins'].std()

print('Mean: ',mean)
print('Std: ',std)

response_timeDataset['Request_Closing_Time_mins'].sort_values().tail()
```

```
Mean:  251.3445353751121
Std:  349.55569222829376
```

[50]:
```
12168     13402.200000
21268     31155.266667
23664     34641.100000
339204    35232.100000
244488    35572.366667
```

```
Name: Request_Closing_Time_mins, dtype: float64
```

[51]:
```
#As we can see, some of the closing times are too high and hence will be dealt␣
↪as outliers.
#We will convert the Request Closing time to normal z statistics and will␣
↪remove any record having value more than 1.
#z-statistic = (value-mean)/std
#Next we will plot the histogram of our Request_Closing_Time_mins.

plot_data = response_timeDataset[␣
↪((response_timeDataset['Request_Closing_Time_mins']-mean)/std) < 1]
plot_data['Request_Closing_Time_mins'].hist(bins=9)
plt.xlabel('Time(mins) to close the request')
plt.ylabel('Number of Requets')
plt.title('Requests closing time distribution')
plt.show()
```



- Above distribution shows that around half of overall complaints were closed within 2 to 3 hours (within approx 250 minutes) .
- Around 99% of the complaints were closed within 10 (600 mins) hours.

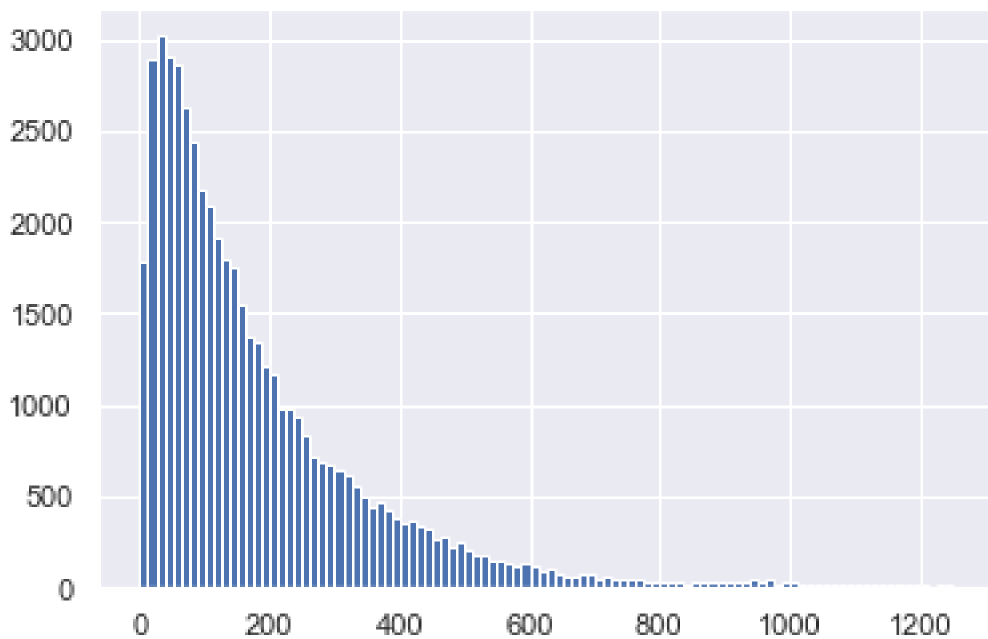
8 Hypothesis testing -

9 check if the average response time across complaint types is similar or not (overall)

- Below is the distribution of our Request_Closing_Time_mins data for 'Noise - Street/Sidewalk' complaint type.
- We see a positive skewness in data if we limit the range to 1250As our data contains too many outliers ,
- hence we will transform the data using log transformation

[52]:
```
df_data = response_timeDataset[response_timeDataset['Complaint_Type']=='Noise -␣
↪Street/Sidewalk']['Request_Closing_Time_mins']
df_data.hist(bins=100,range=(0,1250))
```

[52]: <AxesSubplot:>



[53]:
```
df_data.describe()
```

[53]:
```
count    50823.000000
mean       203.627450
std        320.980463
min          2.283333
25%         58.908333
50%        129.750000
```

```
75%         254.750000
max       35572.366667
Name: Request_Closing_Time_mins, dtype: float64
```

- When we look at above statistics, it becomes clear that we have very few but very large values after th 75th percentile.
- we will take the log of Request_Closing_Minutes for each complaint type and store in a dictionary.
- Log transformation removes the skewness from the data.

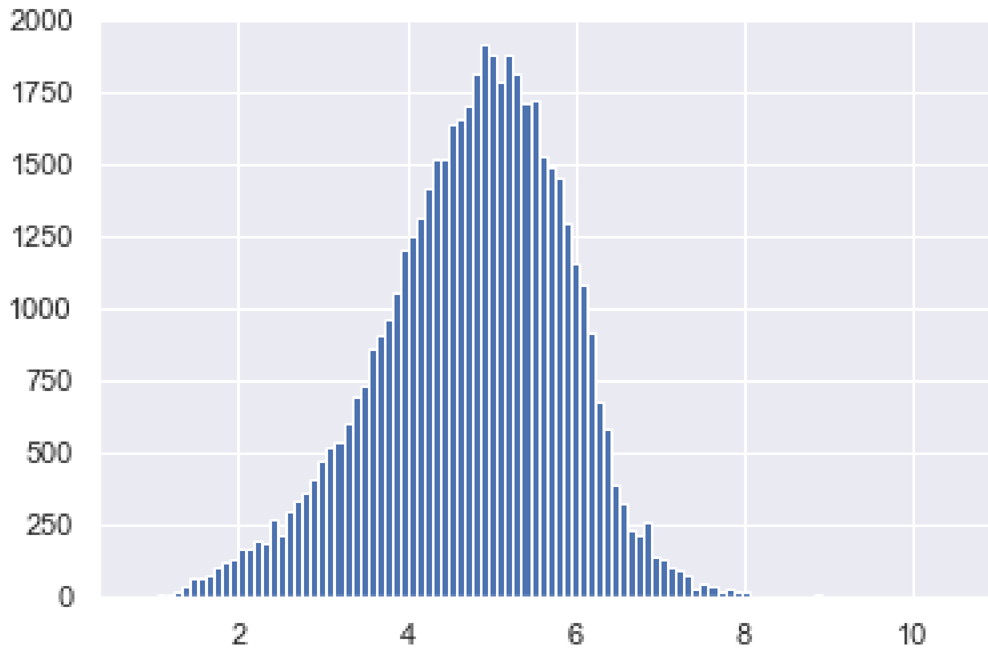
[54]:
```python
# apply the log ransformation

dataset = {}
for i in response_timeDataset['Complaint_Type'].unique():
    dataset[i] = np.
 ↪log(response_timeDataset[response_timeDataset['Complaint_Type']==i]['Request_Closing_Time_m
```

[55]:
```python
dataset.keys()
```

[55]:
```
dict_keys(['Noise - Street/Sidewalk', 'Blocked Driveway', 'Illegal Parking',
'Derelict Vehicle', 'Noise - Commercial', 'Noise - House of Worship', 'Posting
Advertisement', 'Noise - Vehicle', 'Animal Abuse', 'Vending', 'Traffic',
'Drinking', 'Bike/Roller/Skate Chronic', 'Panhandling', 'Noise - Park',
'Homeless Encampment', 'Urinating in Public', 'Graffiti', 'Disorderly Youth',
'Illegal Fireworks', 'Squeegee'])
```

[56]:
```python
dataset['Noise - Street/Sidewalk'].hist(bins=100)
```

[56]: <AxesSubplot:>



Above distribution plot shows that once we apply log Transformation to our data, skewness is almost removed and it looks more like a normal distribution.

[57]:
```
for i in dataset.keys():
    print(dataset[i].std())
```

```
1.1036040708122021
0.9647416380698135
1.0738630624402232
1.2451966392718254
1.0906599622205226
1.1715553703648787
1.225375097478507
1.0793559475623973
1.036449630563194
1.1142164451074161
1.1836120651147704
1.0485525545629217
1.1560390469186679
1.0830431072647795
1.1209874083561666
1.0294588318884546
1.098349150897439
1.0093473489139961
1.034012824402592
1.2135323624143437
```

```
0.8472414281382027
```

Standard deviation for all groups are almost same

- To conduct our hypothesis test, we will conduct an ANOVA (analysis of variance) test as we have to compare the means of more than two groups.
  - Below conditions should be met before conducting ANOVA.
  - All distributions must follow a normal distributions curve. We have verified this after the log transformation
  - Standard deviation for all groups must be same. Above output proves that this is true.
  - All samples are drawn independently of each other.
- Null Hypothesis: Average response time for all the complaints type is same.
- Alternate Hypothesis: Average response time for all the complaints type is not same and theres is some difference among the groups.
  - Below We conduct ANOVA test for top 5 type of complaints
  - For a 95% of confidence interval we choose our alpha as 0.05 for 5%
  - Alpha(0.05) is the critical p-value, if our calculated p-value is less than alpha, it will give us strong evidence to reject Null Hypothesis.
- if $p < alpha(0.05)$: Reject Null Hypothesis, Average response time for all the complaints type is not same.
- if $p > alpha(0.05)$: Fail to reject Null Hypothesis, Average response time for all the complaints type is same.

[58]:
```python
stat, p = f_oneway(dataset['Noise - Street/Sidewalk'],dataset['Blocked␣
↪Driveway'],dataset['Illegal Parking'],dataset['Derelict Vehicle'],
                      dataset['Noise - Commercial'])
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Same distributions (fail to reject H0)')
else:
    print('Different distributions (reject H0)')
```

```
Statistics=2814.991, p=0.000
Different distributions (reject H0)
```

- Conclusion -

Since our p-value is lower tahn alpha, we will conclude that we have enogh evidence to reject pur Null Hypothesis and that Average response time for all the complaints type is not same.

[59]:
```python
''' Assignment is completed! '''
```

[59]: ' Assignment is completed! '

[ ]:
```python

```