

Project: 311 NYC service request.

Importing the Libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

Importing the NYC Dataset

In [2]:

```
data = pd.read_csv('NYC.csv')
```

Convert the Date columns into the datetime datatypes # Below the Date columns is in object datatype initial

In [3]:

data.dtypes

Out[3]:

Unique Key	int64
Created Date	object
Closed Date	object
Agency	object
Agency Name	object
Complaint Type	object
Descriptor	object
Location Type	object
Incident Zip	float64
Incident Address	object
Street Name	object
Cross Street 1	object
Cross Street 2	object
Intersection Street 1	object
Intersection Street 2	object
Address Type	object
City	object
Landmark	object
Facility Type	object
Status	object
Due Date	object
Resolution Description	object
Resolution Action Updated Date	object
Community Board	object
Borough	object
X Coordinate (State Plane)	float64
Y Coordinate (State Plane)	float64
Park Facility Name	object
Park Borough	object
School Name	object
School Number	object
School Region	object
School Code	object
School Phone Number	object
School Address	object
School City	object
School State	object
School Zip	object
School Not Found	object
School or Citywide Complaint	float64
Vehicle Type	float64
Taxi Company Borough	float64
Taxi Pick Up Location	float64
Bridge Highway Name	object
Bridge Highway Direction	object
Road Ramp	object
Bridge Highway Segment	object
Garage Lot Name	float64
Ferry Direction	object
Ferry Terminal Name	object
Latitude	float64
Longitude	float64
Location	object
dtype:	object

In [4]:

```
# Converting the Date columns into the datetime datatypes  
data['Closed Date'] = pd.to_datetime(data['Closed Date'])  
data['Created Date'] = pd.to_datetime(data['Created Date'])
```

In [5]:

data.dtypes

Out[5]:

Unique Key	int64
Created Date	datetime64[ns]
Closed Date	datetime64[ns]
Agency	object
Agency Name	object
Complaint Type	object
Descriptor	object
Location Type	object
Incident Zip	float64
Incident Address	object
Street Name	object
Cross Street 1	object
Cross Street 2	object
Intersection Street 1	object
Intersection Street 2	object
Address Type	object
City	object
Landmark	object
Facility Type	object
Status	object
Due Date	object
Resolution Description	object
Resolution Action Updated Date	object
Community Board	object
Borough	object
X Coordinate (State Plane)	float64
Y Coordinate (State Plane)	float64
Park Facility Name	object
Park Borough	object
School Name	object
School Number	object
School Region	object
School Code	object
School Phone Number	object
School Address	object
School City	object
School State	object
School Zip	object
School Not Found	object
School or Citywide Complaint	float64
Vehicle Type	float64
Taxi Company Borough	float64
Taxi Pick Up Location	float64
Bridge Highway Name	object
Bridge Highway Direction	object
Road Ramp	object
Bridge Highway Segment	object
Garage Lot Name	float64
Ferry Direction	object
Ferry Terminal Name	object
Latitude	float64
Longitude	float64
Location	object
dtype:	object

In [6]:

```
import datetime as dt
```

In [7]:

```
# Renaming the Created Date and Closed Date to Created_Date and Closed_Date
data.rename(columns={'Created Date': 'Created_Date', 'Closed Date': 'Closed_Date',
                    'Complaint Type': 'Complaint_Type', 'Location Type': 'Location_Type'}, inplace = True)
)
```

In [8]:

```
# The time elapsed between the Created_Date and Closed_Date in seconds
time_elapsed = (data.Created_Date - data.Closed_Date).dt.total_seconds()
```

In [9]:

```
# The time in absolute as time can't be negative
t = abs(time_elapsed)
```

In [10]:

```
# Creating the new column Request_closing time in the dataset
data['Request_Closing_Time'] = t
```

In [11]:

```
data.head()
```

Out[11]:

	Unique Key	Created_Date	Closed_Date	Agency	Agency Name	Complaint_Type	Descriptor
0	32310363	2015-12-31 23:59:45	2016-01-01 00:55:15	NYPD	New York City Police Department	Noise - Street/Sidewalk	Loud Music/Party
1	32309934	2015-12-31 23:59:44	2016-01-01 01:26:57	NYPD	New York City Police Department	Blocked Driveway	No Access
2	32309159	2015-12-31 23:59:29	2016-01-01 04:51:03	NYPD	New York City Police Department	Blocked Driveway	No Access
3	32305098	2015-12-31 23:57:46	2016-01-01 07:43:13	NYPD	New York City Police Department	Illegal Parking	Commercial Overnight Parking
4	32306529	2015-12-31 23:56:58	2016-01-01 03:24:42	NYPD	New York City Police Department	Illegal Parking	Blocked Sidewalk

5 rows × 54 columns

Data Understanding and Exploration

Here we are exploration and understanding the dataset and finding the meaningful information from the dataset

info() gives the information of structure of the dataset

like how many rows and columns is in the dataset which variable

is having the null value and what is the datatype of each variables

In [12]:

```
data.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 364558 entries, 0 to 364557
Data columns (total 54 columns):
Unique Key                364558 non-null int64
Created_Date              364558 non-null datetime64[ns]
Closed_Date              362177 non-null datetime64[ns]
Agency                  364558 non-null object
Agency Name             364558 non-null object
Complaint_Type           364558 non-null object
Descriptor               358057 non-null object
Location_Type            364425 non-null object
Incident Zip             361560 non-null float64
Incident Address         312859 non-null object
Street Name              312859 non-null object
Cross Street 1           307370 non-null object
Cross Street 2           306753 non-null object
Intersection Street 1    51120 non-null object
Intersection Street 2    50512 non-null object
Address Type             361306 non-null object
City                     361561 non-null object
Landmark                 375 non-null object
Facility Type            362169 non-null object
Status                   364558 non-null object
Due Date                 364555 non-null object
Resolution Description    364558 non-null object
Resolution Action Updated Date 362156 non-null object
Community Board          364558 non-null object
Borough                  364558 non-null object
X Coordinate (State Plane) 360528 non-null float64
Y Coordinate (State Plane) 360528 non-null float64
Park Facility Name       364558 non-null object
Park Borough             364558 non-null object
School Name              364558 non-null object
School Number            364558 non-null object
School Region            364557 non-null object
School Code              364557 non-null object
School Phone Number      364558 non-null object
School Address           364558 non-null object
School City              364558 non-null object
School State             364558 non-null object
School Zip               364557 non-null object
School Not Found         364558 non-null object
School or Citywide Complaint 0 non-null float64
Vehicle Type             0 non-null float64
Taxi Company Borough     0 non-null float64
Taxi Pick Up Location     0 non-null float64
Bridge Highway Name      297 non-null object
Bridge Highway Direction 297 non-null object
Road Ramp                262 non-null object
Bridge Highway Segment   262 non-null object
Garage Lot Name          0 non-null float64
Ferry Direction          1 non-null object
Ferry Terminal Name      2 non-null object
Latitude                 360528 non-null float64
Longitude                360528 non-null float64
Location                 360528 non-null object
Request_Closing_Time     362177 non-null float64
dtypes: datetime64[ns](2), float64(11), int64(1), object(40)
memory usage: 150.2+ MB

```


Describe() gives the information of the statistic of each numerical variable

like no. of count,mean of the column, standard deviation and min value

1st Quartile,2nd Quartile and 3rd Quartile and max value to see the insight of the dataset

In [13]:

```
data.describe()
```

Out[13]:

	Unique Key	Incident Zip	X Coordinate (State Plane)	Y Coordinate (State Plane)	School or Citywide Complaint	Vehicle Type	Corr Boi
count	3.645580e+05	361560.000000	3.605280e+05	360528.000000	0.0	0.0	
mean	3.106595e+07	10858.496659	1.005043e+06	203425.305782	NaN	NaN	
std	7.331531e+05	578.263114	2.196362e+04	29842.192857	NaN	NaN	
min	2.960737e+07	83.000000	9.133570e+05	121185.000000	NaN	NaN	
25%	3.049938e+07	10314.000000	9.919460e+05	182945.000000	NaN	NaN	
50%	3.108795e+07	11209.000000	1.003470e+06	201023.000000	NaN	NaN	
75%	3.167433e+07	11238.000000	1.019134e+06	222790.000000	NaN	NaN	
max	3.231065e+07	11697.000000	1.067186e+06	271876.000000	NaN	NaN	

In [14]:

```
# head gives the top five rows how the dataset looks like
data.head()
```

Out[14]:

	Unique Key	Created_Date	Closed_Date	Agency	Agency Name	Complaint_Type	Descriptor	I
0	32310363	2015-12-31 23:59:45	2016-01-01 00:55:15	NYPD	New York City Police Department	Noise - Street/Sidewalk	Loud Music/Party	S
1	32309934	2015-12-31 23:59:44	2016-01-01 01:26:57	NYPD	New York City Police Department	Blocked Driveway	No Access	S
2	32309159	2015-12-31 23:59:29	2016-01-01 04:51:03	NYPD	New York City Police Department	Blocked Driveway	No Access	S
3	32305098	2015-12-31 23:57:46	2016-01-01 07:43:13	NYPD	New York City Police Department	Illegal Parking	Commercial Overnight Parking	S
4	32306529	2015-12-31 23:56:58	2016-01-01 03:24:42	NYPD	New York City Police Department	Illegal Parking	Blocked Sidewalk	S

5 rows × 54 columns

In [15]:

```
# columns gives the name of each variables in the dataset
data.columns
```

Out[15]:

```
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',
      'Request_Closing_Time'],
      dtype='object')
```

In [16]:

```
# nunique() counts the no. of unique values in the columns  
data.nunique()
```

Out[16]:

Unique Key	364558
Created_Date	362018
Closed_Date	339837
Agency	1
Agency Name	3
Complaint_Type	24
Descriptor	45
Location_Type	18
Incident Zip	201
Incident Address	126372
Street Name	7693
Cross Street 1	6234
Cross Street 2	6064
Intersection Street 1	4704
Intersection Street 2	4422
Address Type	5
City	53
Landmark	120
Facility Type	1
Status	4
Due Date	362015
Resolution Description	18
Resolution Action Updated Date	340833
Community Board	75
Borough	6
X Coordinate (State Plane)	68410
Y Coordinate (State Plane)	79924
Park Facility Name	2
Park Borough	6
School Name	2
School Number	2
School Region	1
School Code	1
School Phone Number	2
School Address	2
School City	2
School State	2
School Zip	1
School Not Found	1
School or Citywide Complaint	0
Vehicle Type	0
Taxi Company Borough	0
Taxi Pick Up Location	0
Bridge Highway Name	29
Bridge Highway Direction	34
Road Ramp	2
Bridge Highway Segment	187
Garage Lot Name	0
Ferry Direction	1
Ferry Terminal Name	2
Latitude	146714
Longitude	146472
Location	146751
Request_Closing_Time	56190
dtype: int64	

In [17]:

```
# sns.swarmplot(x="Agency Name", y="Request_Closing_Time", data=data)
```

Correlation heatmap show the relation between the numerical variables

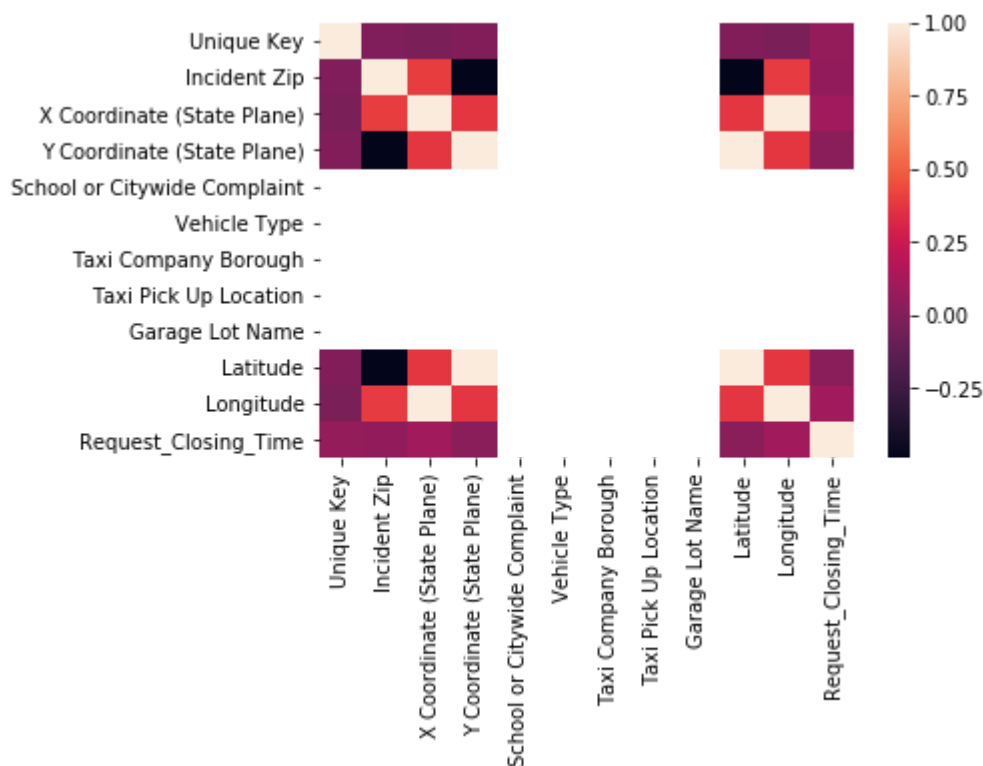
Here in this map states thatn the location are highly corelated with each other

In [18]:

```
sns.heatmap(data.corr())
```

Out[18]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a233bff60>



In [19]:

```
# How many null values contains in each variables  
data.isnull().sum()
```

Out[19]:

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
Request_Closing_Time	2381

dtype: int64

In [20]:

```
data.head()
```

Out[20]:

	Unique Key	Created_Date	Closed_Date	Agency	Agency Name	Complaint_Type	Descriptor	L
0	32310363	2015-12-31 23:59:45	2016-01-01 00:55:15	NYPD	New York City Police Department	Noise - Street/Sidewalk	Loud Music/Party	S
1	32309934	2015-12-31 23:59:44	2016-01-01 01:26:57	NYPD	New York City Police Department	Blocked Driveway	No Access	S
2	32309159	2015-12-31 23:59:29	2016-01-01 04:51:03	NYPD	New York City Police Department	Blocked Driveway	No Access	S
3	32305098	2015-12-31 23:57:46	2016-01-01 07:43:13	NYPD	New York City Police Department	Illegal Parking	Commercial Overnight Parking	S
4	32306529	2015-12-31 23:56:58	2016-01-01 03:24:42	NYPD	New York City Police Department	Illegal Parking	Blocked Sidewalk	S

5 rows × 54 columns

In [21]:

```
# pivot table to show the relation between Complaint Type and Agency type with Request Closing Time
pv = data.pivot_table(values='Request_Closing_Time', index='Complaint_Type', columns='Agency Name')
```

Analysis of pivot table heatmap

heatmap plot show that Animal in a Park has the highest complaint through New York City Police Department at request closing time above 1000000

Most of the complaint is coming through New York City Police with a request closing time of 250000 seconds

Blocked Driveway complaint is coming from NYPD with request closing time of 250000 seconds

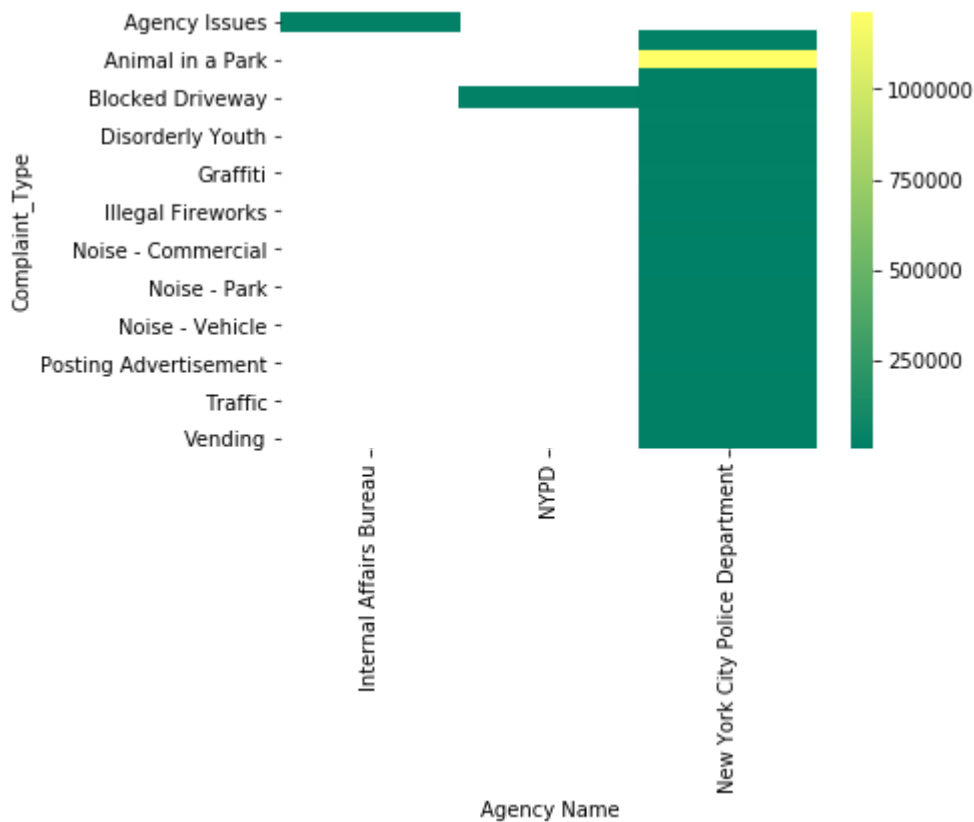
Agency Issues complaint is coming from NYPD with request closing time of 250000 seconds

In [22]:

```
sns.heatmap(pv,cmap = 'summer')
```

Out[22]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a2b9657f0>



Order the complaint types based on the average 'Request_Closing_Time' grouping them for different locations.

In [23]:

```
d = data[['Complaint_Type', 'Request_Closing_Time', 'Location', 'Location_Type', 'Incident Address']]
d.head()
```

Out[23]:

	Complaint_Type	Request_Closing_Time	Location	Location_Type	Incident Address
0	Noise - Street/Sidewalk	3330.0	(40.86568153633767, -73.92350095571744)	Street/Sidewalk	71 VERMILYEA AVENUE
1	Blocked Driveway	5233.0	(40.775945312321085, -73.91509393898605)	Street/Sidewalk	27-07 23 AVENUE
2	Blocked Driveway	17494.0	(40.870324522111424, -73.88852464418646)	Street/Sidewalk	2897 VALENTINE AVENUE
3	Illegal Parking	27927.0	(40.83599404683083, -73.82837939584206)	Street/Sidewalk	2940 BAISLEY AVENUE
4	Illegal Parking	12464.0	(40.733059618956815, -73.87416975810375)	Street/Sidewalk	87-14 57 ROAD

In [24]:

```
location_based=d.groupby(['Location_Type', 'Incident Address', 'Complaint_Type', 'Location'], as_index = True).mean()
```

Different Location Based groupby with complaint type on the bases of aVerage Request closing time

In [25]:

```
location_based.head(30)
```

Out[25]:

				Request_Closing_Ti
Location_Type	Incident Address	Complaint_Type	Location	
Club/Bar/Restaurant	1 AVENUE	Noise - Commercial	(40.723586990296035, -73.98820272801426)	6725.0000
			(40.72728112699584, -73.98551777527184)	1607.0000
			(40.75929883744741, -73.9621996109738)	1784.0000
			(40.77070570077645, -73.95388226861742)	6279.0000
			(40.77460754303029, -73.95103088743048)	17314.3333
			(40.77524412627464, -73.9505718823054)	2658.0000
	1 BAY CLUB DRIVE	Noise - Commercial	(40.779012083546895, -73.78208491752011)	1457.0000
	1 BEDFORD AVENUE	Noise - Commercial	(40.72400263455818, -73.95106807164736)	11479.0000
	1 BENNETT AVENUE	Noise - Commercial	(40.850728062663016, -73.93650911771923)	9518.0000
	1 CHURCH STREET	Noise - Commercial	(40.70978635563814, -74.01159644552898)	9547.0000
	1 DOWNING STREET	Noise - Commercial	(40.729683669819636, -74.00260141017563)	34886.0000
	1 EAST 184 STREET	Noise - Commercial	(40.8605385231975, -73.90240518642987)	12962.0000
	1 EAST 67 STREET	Noise - Commercial	(40.76917648218226, -73.96911836496761)	13733.0000
	1 FDR FOUR FREEDOMS PARK	Noise - Commercial	(40.75146432780528, -73.95925169945215)	3506.0000
	1 LITTLE WEST 12 STREET	Noise - Commercial	(40.73945486717447, -74.00597582111745)	16817.0000
	1 LUDLOW STREET	Noise - Commercial	(40.71457895713592, -73.99119111783705)	2662.0000
	1 MARGARET CORBIN DRIVE	Noise - Commercial	(40.860900383158516, -73.93247571308034)	15686.5000
	1 NAGLE AVENUE	Noise - Commercial	(40.85932419390543, -73.93123733660875)	18413.3024
	1 NELSON AVENUE	Noise - Commercial	(40.54983696336894, -74.15079600753874)	5181.3333
	1 PENN PLAZA	Noise - Commercial	(40.75065872876379, -73.99087595619766)	8251.0000

Location_Type	Incident Address	Complaint_Type	Location	
	1 SOUTH OXFORD STREET	Noise - Commercial	(40.689310796391844, -73.97403049606427)	9868.0000
	1 STATION SQUARE	Noise - Commercial	(40.71924029726528, -73.84532504397058)	6791.6660
	1 TENNIS PLACE	Noise - Commercial	(40.719006004974794, -73.84663871262093)	482.0000
	1 WEST 35 STREET	Noise - Commercial	(40.749302146077014, -73.9845313071452)	4210.0000
	10 AKRON STREET	Drinking	(40.61173799306301, -74.15883073802867)	15806.0000
	10 AVENUE	Noise - Commercial	(40.76123719758523, -73.99430017671288)	13813.0000
			(40.86227061005415, -73.9205259107025)	9990.5000
	10 DELANCEY STREET	Drinking	(40.72016744276424, -73.99351002956226)	27184.0000
	10 DESBROSSES STREET	Noise - Commercial	(40.72335396551203, -74.00864769481181)	1864.0000
	10 DOWNING STREET	Noise - Commercial	(40.72959583237184, -74.00282510607859)	11564.4230

Hypothesis Testing

Perform statistical test for the following: Please note: For the below statements you need to state the Null and Alternate and then provide a statistical test to accept or reject the Null Hypothesis along with the corresponding 'p value'. Whether the average response time across complaint types are similar or not (overall) Is the type of complaint or service requested and location related?

Hypothesis for First Statement:-

Null Hypothesis : The average response time across complaint types are similar

Alternate Hypothesis : The average response time across complaint types are not same

In [26]:

```
data.describe()
```

Out[26]:

	Unique Key	Incident Zip	X Coordinate (State Plane)	Y Coordinate (State Plane)	School or Citywide Complaint	Vehicle Type	T Comp Borou
count	3.645580e+05	361560.000000	3.605280e+05	360528.000000	0.0	0.0	
mean	3.106595e+07	10858.496659	1.005043e+06	203425.305782	NaN	NaN	N
std	7.331531e+05	578.263114	2.196362e+04	29842.192857	NaN	NaN	N
min	2.960737e+07	83.000000	9.133570e+05	121185.000000	NaN	NaN	N
25%	3.049938e+07	10314.000000	9.919460e+05	182945.000000	NaN	NaN	N
50%	3.108795e+07	11209.000000	1.003470e+06	201023.000000	NaN	NaN	N
75%	3.167433e+07	11238.000000	1.019134e+06	222790.000000	NaN	NaN	N
max	3.231065e+07	11697.000000	1.067186e+06	271876.000000	NaN	NaN	N

In [27]:

```
# Importing the stats model ols
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

In [28]:

```
#variable ~ treatment
mod = ols('Request_Closing_Time~Complaint_Type', data=data).fit()
```

In [29]:

```
data.Request_Closing_Time.isnull().sum()
```

Out[29]:

2381

In [30]:

```
from sklearn.preprocessing import Imputer
imputer = Imputer(missing_values="NaN", strategy="mean", axis=0)
data[['Request_Closing_Time']] = imputer.fit_transform(data[['Request_Closing_Time']])
```

```
/anaconda3/lib/python3.6/site-packages/sklearn/utils/deprecation.py:
58: DeprecationWarning: Class Imputer is deprecated; Imputer was deprecated in version 0.20 and will be removed in 0.22. Import impute.SimpleImputer from sklearn instead.
warnings.warn(msg, category=DeprecationWarning)
```

In [31]:

```
data.Request_Closing_Time.isnull().sum()
```

Out[31]:

0

In [32]:

```
# Summary of the anova test  
mod.summary()
```

Out[32]:

OLS Regression Results

Dep. Variable:	Request_Closing_Time	R-squared:	0.033
Model:	OLS	Adj. R-squared:	0.033
Method:	Least Squares	F-statistic:	565.3
Date:	Fri, 08 Mar 2019	Prob (F-statistic):	0.00
Time:	20:44:39	Log-Likelihood:	-4.1140e+06
No. Observations:	362177	AIC:	8.228e+06
Df Residuals:	362154	BIC:	8.228e+06
Df Model:	22		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
Intercept	1.829e+04	7336.210	2.493	0.013	3910.369	3.27e+04
Complaint_Type[T.Animal Abuse]	-256.5690	7338.997	-0.035	0.972	-1.46e+04	1.41e+04
Complaint_Type[T.Animal in a Park]	1.194e+06	2.2e+04	54.267	0.000	1.15e+06	1.24e+06
Complaint_Type[T.Bike/Roller/Skate Chronic]	-5165.4366	7397.731	-0.698	0.485	-1.97e+04	9333.898
Complaint_Type[T.Blocked Driveway]	-2056.6035	7336.502	-0.280	0.779	-1.64e+04	1.23e+04
Complaint_Type[T.Derelict Vehicle]	7070.4751	7337.574	0.964	0.335	-7310.954	2.15e+04
Complaint_Type[T.Disorderly Youth]	-5925.3758	7428.785	-0.798	0.425	-2.05e+04	8634.823
Complaint_Type[T.Drinking]	-4467.8244	7357.082	-0.607	0.544	-1.89e+04	9951.839
Complaint_Type[T.Ferry Complaint]	2.892e-10	1.12e-10	2.589	0.010	7.03e-11	5.08e-10
Complaint_Type[T.Graffiti]	4987.2189	7520.798	0.663	0.507	-9753.324	1.97e+04
Complaint_Type[T.Homeless Encampment]	-2837.7405	7342.222	-0.386	0.699	-1.72e+04	1.16e+04
Complaint_Type[T.Illegal Fireworks]	-8175.6424	7504.881	-1.089	0.276	-2.29e+04	6533.703
Complaint_Type[T.Illegal Parking]	-2638.6893	7336.530	-0.360	0.719	-1.7e+04	1.17e+04
Complaint_Type[T.Noise - Commercial]	-7203.3645	7336.881	-0.982	0.326	-2.16e+04	7176.706
Complaint_Type[T.Noise - House of Worship]	-6898.0379	7363.636	-0.937	0.349	-2.13e+04	7534.471
Complaint_Type[T.Noise - Park]	-6063.0695	7343.383	-0.826	0.409	-2.05e+04	8329.746
Complaint_Type[T.Noise - Street/Sidewalk]	-6057.8296	7336.784	-0.826	0.409	-2.04e+04	8322.051
Complaint_Type[T.Noise - Vehicle]	-5727.3250	7337.731	-0.781	0.435	-2.01e+04	8654.411
Complaint_Type[T.Panhandling]	-2435.5742	7425.953	-0.328	0.743	-1.7e+04	1.21e+04
Complaint_Type[T.Posting Advertisement]	-1.1e+04	7379.302	-1.491	0.136	-2.55e+04	3460.345
Complaint_Type[T.Squeegee]	-3728.8750	1.27e+04	-0.293	0.769	-2.86e+04	2.12e+04

Complaint_Type[T.Traffic]	-5980.0049	7341.856	-0.815	0.415	-2.04e+04	8409.816
Complaint_Type[T.Urinating in Public]	-5329.8317	7381.848	-0.722	0.470	-1.98e+04	9138.373
Complaint_Type[T.Vending]	-3922.8466	7343.219	-0.534	0.593	-1.83e+04	1.05e+04
Omnibus:	742266.863	Durbin-Watson:	1.932			
Prob(Omnibus):	0.000	Jarque-Bera (JB):	19220029680.906			
Skew:	16.400	Prob(JB):	0.00			
Kurtosis:	1131.077	Cond. No.	8.89e+16			

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The smallest eigenvalue is 5.46e-29. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

In [33]:

```
aov_table = sm.stats.anova_lm(mod)
```

In [34]:

```
aov_table
```

Out[34]:

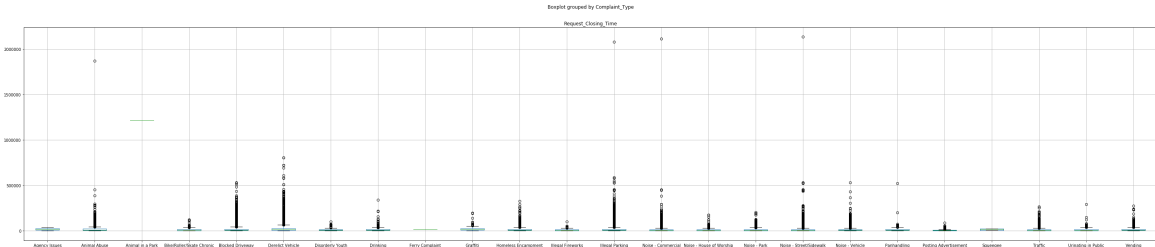
	df	sum_sq	mean_sq	F	PR(>F)
Complaint_Type	23.0	5.354568e+12	2.328073e+11	540.708285	0.0
Residual	362154.0	1.559290e+14	4.305599e+08	NaN	NaN

In [35]:

```
# double click for zoom the plot show the variance relation between Request closing time and complaint type
data.boxplot('Request_Closing_Time',by = 'Complaint_Type',figsize = (50,10),rot =0)
```

Out[35]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a2942e748>



In [36]:

```
# Tukey method show
```

In [37]:

```
from statsmodels.stats.multicomp import pairwise_tukeyhsd
```

In [38]:

```
tukey = pairwise_tukeyhsd(data.Request_Closing_Time, data.Complaint_Type, alpha  
= 0.05)
```

In [39]:

```
tukey.summary()
```

Out[39]:

Multiple Comparison of Means - Tukey HSD,FWER=0.05

group1	group2	meandiff	lower	upper	reject
Agency Issues	Animal Abuse	-259.6153	-26869.5281	26350.2974	False
Agency Issues	Animal in a Park	1194344.875	1114545.4125	1274144.3375	True
Agency Issues	Bike/Roller/Skate Chronic	-5152.9495	-31974.4393	21668.5404	False
Agency Issues	Blocked Driveway	-2059.4548	-28660.3303	24541.4208	False
Agency Issues	Derelict Vehicle	7002.8318	-19601.9006	33607.5642	False
Agency Issues	Disorderly Youth	-5925.3758	-32860.8543	21010.1028	False
Agency Issues	Drinking	-4463.2396	-31138.4676	22211.9884	False
Agency Issues	Ferry Complaint	-3175.8254	-62654.833	56303.1822	False
Agency Issues	Graffiti	4987.2189	-22281.8844	32256.3223	False
Agency Issues	Homeless Encampment	-2837.7405	-29459.36	23783.879	False
Agency Issues	Illegal Fireworks	-8175.6424	-35387.0333	19035.7484	False
Agency Issues	Illegal Parking	-2644.2706	-29245.2394	23956.6983	False
Agency Issues	Noise - Commercial	-7170.6759	-33772.9088	19431.557	False
Agency Issues	Noise - House of Worship	-6891.0805	-33590.1548	19807.9937	False
Agency Issues	Noise - Park	-6049.0162	-32674.7187	20576.6862	False
Agency Issues	Noise - Street/Sidewalk	-6026.998	-32628.8771	20574.8811	False
Agency Issues	Noise - Vehicle	-5720.6008	-32325.9192	20884.7176	False
Agency Issues	Panhandling	-2440.1018	-29363.3366	24483.133	False
Agency Issues	Posting Advertisement	-10979.8818	-37735.4863	15775.7226	False
Agency Issues	Squeegee	-3728.875	-49801.1162	42343.3662	False
Agency Issues	Traffic	-5978.926	-32599.2082	20641.3563	False
Agency Issues	Urinating in Public	-5329.8317	-32095.1274	21435.464	False
Agency Issues	Vending	-3921.5992	-30546.7895	22703.591	False
Animal Abuse	Animal in a Park	1194604.4903	1119365.2669	1269843.7138	True
Animal Abuse	Bike/Roller/Skate Chronic	-4893.3341	-8411.6914	-1374.9768	True
Animal Abuse	Blocked Driveway	-1799.8394	-2569.9686	-1029.7102	True
Animal Abuse	Derelict Vehicle	7262.4472	6368.9669	8155.9274	True
Animal Abuse	Disorderly Youth	-5665.7605	-9967.6815	-1363.8394	True
Animal Abuse	Drinking	-4203.6243	-6337.707	-2069.5415	True
Animal Abuse	Ferry Complaint	-2916.21	-56120.8984	50288.4783	False
Animal Abuse	Graffiti	5246.8343	-802.1752	11295.8438	False
Animal Abuse	Homeless Encampment	-2578.1252	-3880.8706	-1275.3797	True

Animal Abuse	Illegal Fireworks	-7916.0271	-13699.3059	-2132.7483	True
Animal Abuse	Illegal Parking	-2384.6552	-3158.0016	-1611.3088	True
Animal Abuse	Noise - Commercial	-6911.0606	-7726.7302	-6095.391	True
Animal Abuse	Noise - House of Worship	-6631.4652	-9045.401	-4217.5293	True
Animal Abuse	Noise - Park	-5789.4009	-7173.0741	-4405.7276	True
Animal Abuse	Noise - Street/Sidewalk	-5767.3826	-6571.4297	-4963.3355	True
Animal Abuse	Noise - Vehicle	-5460.9855	-6371.7469	-4550.224	True
Animal Abuse	Panhandling	-2180.4864	-6405.0683	2044.0955	False
Animal Abuse	Posting Advertisement	-10720.2665	-13694.9747	-7745.5583	True
Animal Abuse	Squeegee	-3469.2597	-41094.2238	34155.7045	False
Animal Abuse	Traffic	-5719.3106	-6994.437	-4444.1842	True
Animal Abuse	Urinating in Public	-5070.2164	-8130.8654	-2009.5674	True
Animal Abuse	Vending	-3661.9839	-5035.7657	-2288.2021	True
Animal in a Park	Bike/Roller/Skate Chronic	-1199497.8245	-1274812.1365	-1124183.5124	True
Animal in a Park	Blocked Driveway	-1196404.3298	-1271640.3574	-1121168.3021	True
Animal in a Park	Derelict Vehicle	-1187342.0432	-1262579.4346	-1112104.6517	True
Animal in a Park	Disorderly Youth	-1200270.2508	-1275625.2326	-1124915.269	True
Animal in a Park	Drinking	-1198808.1146	-1274070.4629	-1123545.7663	True
Animal in a Park	Ferry Complaint	-1197520.7004	-1289665.1827	-1105376.218	True
Animal in a Park	Graffiti	-1189357.6561	-1264832.5345	-1113882.7776	True
Animal in a Park	Homeless Encampment	-1197182.6155	-1272425.98	-1121939.251	True
Animal in a Park	Illegal Fireworks	-1202520.5174	-1277974.5636	-1127066.4713	True
Animal in a Park	Illegal Parking	-1196989.1456	-1272225.2062	-1121753.0849	True
Animal in a Park	Noise - Commercial	-1201515.5509	-1276752.0585	-1126279.0433	True
Animal in a Park	Noise - House of Worship	-1201235.9555	-1276506.7589	-1125965.1521	True
Animal in a Park	Noise - Park	-1200393.8912	-1275638.7004	-1125149.082	True
Animal in a Park	Noise - Street/Sidewalk	-1200371.873	-1275608.2555	-1125135.4905	True
Animal in a Park	Noise - Vehicle	-1200065.4758	-1275303.0744	-1124827.8772	True
Animal in a Park	Panhandling	-1196784.9768	-1272135.583	-1121434.3706	True
Animal in a Park	Posting Advertisement	-1205324.7568	-1280615.6304	-1130033.8832	True
Animal in a Park	Squeegee	-1198073.75	-1282189.7692	-1113957.7308	True
Animal in a Park	Traffic	-1200323.801	-1275566.6924	-1125080.9095	True
Animal in a Park	Urinating in Public	-1199674.7067	-1274969.0248	-1124380.3886	True
Animal in a Park	Vending	-1198266.4742	-1273511.1022	-1123021.8462	True
Bike/Roller/Skate Chronic	Blocked Driveway	3093.4947	-355.847	6542.8365	False

Bike/Roller/Skate Chronic	Derelict Vehicle	12155.7813	8676.8207	15634.7419	True
Bike/Roller/Skate Chronic	Disorderly Youth	-772.4263	-6232.4066	4687.554	False
Bike/Roller/Skate Chronic	Drinking	689.7099	-3292.6473	4672.067	False
Bike/Roller/Skate Chronic	Ferry Complaint	1977.1241	-51333.6977	55287.9459	False
Bike/Roller/Skate Chronic	Graffiti	10140.1684	3219.5199	17060.8169	True
Bike/Roller/Skate Chronic	Homeless Encampment	2315.209	-1290.6204	5921.0383	False
Bike/Roller/Skate Chronic	Illegal Fireworks	-3022.693	-9712.3247	3666.9388	False
Bike/Roller/Skate Chronic	Illegal Parking	2508.6789	-941.3826	5958.7404	False
Bike/Roller/Skate Chronic	Noise - Commercial	-2017.7264	-5477.5207	1442.0678	False
Bike/Roller/Skate Chronic	Noise - House of Worship	-1738.131	-5877.2065	2400.9444	False
Bike/Roller/Skate Chronic	Noise - Park	-896.0667	-4531.9176	2739.7841	False
Bike/Roller/Skate Chronic	Noise - Street/Sidewalk	-874.0485	-4331.1211	2583.0242	False
Bike/Roller/Skate Chronic	Noise - Vehicle	-567.6513	-4051.0901	2915.7875	False
Bike/Roller/Skate Chronic	Panhandling	2712.8477	-2686.4071	8112.1025	False
Bike/Roller/Skate Chronic	Posting Advertisement	-5826.9323	-10316.225	-1337.6397	True
Bike/Roller/Skate Chronic	Squeegee	1424.0745	-36350.8218	39198.9707	False
Bike/Roller/Skate Chronic	Traffic	-825.9765	-4421.9196	2769.9666	False
Bike/Roller/Skate Chronic	Urinating in Public	-176.8822	-4723.5768	4369.8124	False
Bike/Roller/Skate Chronic	Vending	1231.3503	-2400.7478	4863.4483	False
Blocked Driveway	Derelict Vehicle	9062.2866	8498.8796	9625.6936	True
Blocked Driveway	Disorderly Youth	-3865.921	-8111.583	379.7409	False
Blocked Driveway	Drinking	-2403.7849	-4422.0588	-385.5109	True
Blocked Driveway	Ferry Complaint	-1116.3706	-54316.5396	52083.7984	False
Blocked Driveway	Graffiti	7046.6737	1037.5443	13055.8032	True
Blocked Driveway	Homeless Encampment	-778.2857	-1881.1303	324.5589	False
Blocked Driveway	Illegal Fireworks	-6116.1877	-11857.7409	-374.6344	True
Blocked Driveway	Illegal Parking	-584.8158	-927.1388	-242.4927	True
Blocked Driveway	Noise - Commercial	-5111.2212	-5540.6829	-4681.7595	True

Blocked Driveway	Noise - House of Worship	-4831.6257	-7143.8123	-2519.4392	True
Blocked Driveway	Noise - Park	-3989.5615	-5186.9219	-2792.201	True
Blocked Driveway	Noise - Street/Sidewalk	-3967.5432	-4374.498	-3560.5884	True
Blocked Driveway	Noise - Vehicle	-3661.146	-4251.5754	-3070.7167	True
Blocked Driveway	Panhandling	-380.647	-4547.9258	3786.6318	False
Blocked Driveway	Posting Advertisement	-8920.4271	-11813.1783	-6027.6759	True
Blocked Driveway	Squeegee	-1669.4202	-39287.9934	35949.1529	False
Blocked Driveway	Traffic	-3919.4712	-4989.5496	-2849.3928	True
Blocked Driveway	Urinating in Public	-3270.3769	-6251.4326	-289.3213	True
Blocked Driveway	Vending	-1862.1444	-3048.0605	-676.2284	True
Derelict Vehicle	Disorderly Youth	-12928.2076	-17197.968	-8658.4473	True
Derelict Vehicle	Drinking	-11466.0714	-13534.5583	-9397.5846	True
Derelict Vehicle	Ferry Complaint	-10178.6572	-63380.7548	43023.4404	False
Derelict Vehicle	Graffiti	-2015.6129	-8041.7928	4010.5671	False
Derelict Vehicle	Homeless Encampment	-9840.5723	-11032.8283	-8648.3164	True
Derelict Vehicle	Illegal Fireworks	-15178.4743	-20937.8702	-9419.0783	True
Derelict Vehicle	Illegal Parking	-9647.1024	-10214.8991	-9079.3057	True
Derelict Vehicle	Noise - Commercial	-14173.5078	-14797.7236	-13549.2919	True
Derelict Vehicle	Noise - House of Worship	-13893.9123	-16250.0564	-11537.7683	True
Derelict Vehicle	Noise - Park	-13051.848	-14332.0356	-11771.6605	True
Derelict Vehicle	Noise - Street/Sidewalk	-13029.8298	-13638.7799	-12420.8797	True
Derelict Vehicle	Noise - Vehicle	-12723.4326	-13467.62	-11979.2453	True
Derelict Vehicle	Panhandling	-9442.9336	-13634.7615	-5251.1057	True
Derelict Vehicle	Posting Advertisement	-17982.7137	-20910.7194	-15054.7079	True
Derelict Vehicle	Squeegee	-10731.7068	-48353.0074	26889.5937	False
Derelict Vehicle	Traffic	-12981.7578	-14143.7715	-11819.7441	True
Derelict Vehicle	Urinating in Public	-12332.6635	-15347.9414	-9317.3856	True
Derelict Vehicle	Vending	-10924.431	-12193.9211	-9654.941	True
Disorderly Youth	Drinking	1462.1362	-3226.8782	6151.1505	False
Disorderly Youth	Ferry Complaint	2749.5504	-50618.7118	56117.8126	False
Disorderly Youth	Graffiti	10912.5947	3562.5565	18262.633	True
Disorderly Youth	Homeless Encampment	3087.6353	-1286.1151	7461.3857	False
Disorderly Youth	Illegal Fireworks	-2250.2666	-9383.2085	4882.6752	False
Disorderly Youth	Illegal Parking	3281.1052	-965.1415	7527.3519	False
Disorderly Youth	Noise - Commercial	-1245.3001	-5499.4585	3008.8582	False

Disorderly Youth	Noise - House of Worship	-965.7047	-5788.5289	3857.1194	False
Disorderly Youth	Noise - Park	-123.6404	-4522.1741	4274.8932	False
Disorderly Youth	Noise - Street/Sidewalk	-101.6222	-4353.5674	4150.3231	False
Disorderly Youth	Noise - Vehicle	204.775	-4068.635	4478.185	False
Disorderly Youth	Panhandling	3485.274	-2454.3925	9424.9406	False
Disorderly Youth	Posting Advertisement	-5054.506	-10181.0483	72.0362	False
Disorderly Youth	Squeegee	2196.5008	-35659.4165	40052.4181	False
Disorderly Youth	Traffic	-53.5502	-4419.1536	4312.0533	False
Disorderly Youth	Urinating in Public	595.5441	-4581.339	5772.4272	False
Disorderly Youth	Vending	2003.7766	-2391.6555	6399.2086	False
Drinking	Ferry Complaint	1287.4143	-51949.9711	54524.7996	False
Drinking	Graffiti	9450.4586	3120.3048	15780.6124	True
Drinking	Homeless Encampment	1625.4991	-649.9077	3900.906	False
Drinking	Illegal Fireworks	-3712.4028	-9789.1325	2364.3269	False
Drinking	Illegal Parking	1818.9691	-200.5346	3838.4728	False
Drinking	Noise - Commercial	-2707.4363	-4743.5226	-671.35	True
Drinking	Noise - House of Worship	-2427.8409	-5478.6468	622.965	False
Drinking	Noise - Park	-1585.7766	-3908.4652	736.912	False
Drinking	Noise - Street/Sidewalk	-1563.7583	-3595.2165	467.6999	False
Drinking	Noise - Vehicle	-1257.3612	-3333.3711	818.6487	False
Drinking	Panhandling	2023.1379	-2595.0244	6641.3002	False
Drinking	Posting Advertisement	-6516.6422	-10027.9411	-3005.3433	True
Drinking	Squeegee	734.3646	-36936.8214	38405.5507	False
Drinking	Traffic	-1515.6863	-3775.3938	744.0211	False
Drinking	Urinating in Public	-866.5921	-4450.9892	2717.8051	False
Drinking	Vending	541.6404	-1775.1693	2858.4501	False
Ferry Complaint	Graffiti	8163.0443	-45374.3763	61700.4649	False
Ferry Complaint	Homeless Encampment	338.0849	-52872.4595	53548.6292	False
Ferry Complaint	Illegal Fireworks	-4999.8171	-58507.8651	48508.2309	False
Ferry Complaint	Illegal Parking	531.5548	-52668.6609	53731.7705	False
Ferry Complaint	Noise - Commercial	-3994.8506	-57195.6983	49205.9972	False
Ferry Complaint	Noise - House of Worship	-3715.2551	-56964.5929	49534.0826	False
Ferry Complaint	Noise - Park	-2873.1908	-56085.7781	50339.3964	False
Ferry Complaint	Noise - Street/Sidewalk	-2851.1726	-56051.8434	50349.4982	False

Ferry Complaint	Noise - Vehicle	-2544.7754	-55747.1661	50657.6152	False
Ferry Complaint	Panhandling	735.7236	-52626.3601	54097.8073	False
Ferry Complaint	Posting Advertisement	-7804.0565	-61081.7608	45473.6478	False
Ferry Complaint	Squeegee	-553.0496	-65709.0379	64602.9387	False
Ferry Complaint	Traffic	-2803.1006	-56012.9759	50406.7747	False
Ferry Complaint	Urinating in Public	-2154.0063	-55436.5781	51128.5655	False
Ferry Complaint	Vending	-745.7738	-53958.1048	52466.5571	False
Graffiti	Homeless Encampment	-7824.9594	-13925.2614	-1724.6575	True
Graffiti	Illegal Fireworks	-13162.8614	-21467.2489	-4858.4739	True
Graffiti	Illegal Parking	-7631.4895	-13641.0321	-1621.9469	True
Graffiti	Noise - Commercial	-12157.8949	-18173.0303	-6142.7594	True
Graffiti	Noise - House of Worship	-11878.2995	-18308.2002	-5448.3987	True
Graffiti	Noise - Park	-11036.2352	-17154.3304	-4918.1399	True
Graffiti	Noise - Street/Sidewalk	-11014.2169	-17027.7874	-5000.6465	True
Graffiti	Noise - Vehicle	-10707.8198	-16736.5861	-4679.0534	True
Graffiti	Panhandling	-7427.3207	-14732.3621	-122.2793	True
Graffiti	Posting Advertisement	-15967.1008	-22627.8385	-9306.3631	True
Graffiti	Squeegee	-8716.0939	-46810.1153	29377.9274	False
Graffiti	Traffic	-10966.1449	-17060.6084	-4871.6814	True
Graffiti	Urinating in Public	-10317.0507	-17016.6111	-3617.4902	True
Graffiti	Vending	-8908.8182	-15024.6839	-2792.9524	True
Homeless Encampment	Illegal Fireworks	-5337.9019	-11174.8087	499.0048	False
Homeless Encampment	Illegal Parking	193.4699	-911.6237	1298.5636	False
Homeless Encampment	Noise - Commercial	-4332.9354	-5468.0496	-3197.8213	True
Homeless Encampment	Noise - House of Worship	-4053.34	-6593.0749	-1513.6051	True
Homeless Encampment	Noise - Park	-3211.2757	-4804.2977	-1618.2538	True
Homeless Encampment	Noise - Street/Sidewalk	-3189.2575	-4316.049	-2062.466	True
Homeless Encampment	Noise - Vehicle	-2882.8603	-4088.1211	-1677.5995	True
Homeless Encampment	Panhandling	397.6387	-3900.0653	4695.3427	False
Homeless Encampment	Posting Advertisement	-8142.1413	-11219.8119	-5064.4707	True
Homeless Encampment	Squeegee	-891.1345	-38524.379	36742.11	False

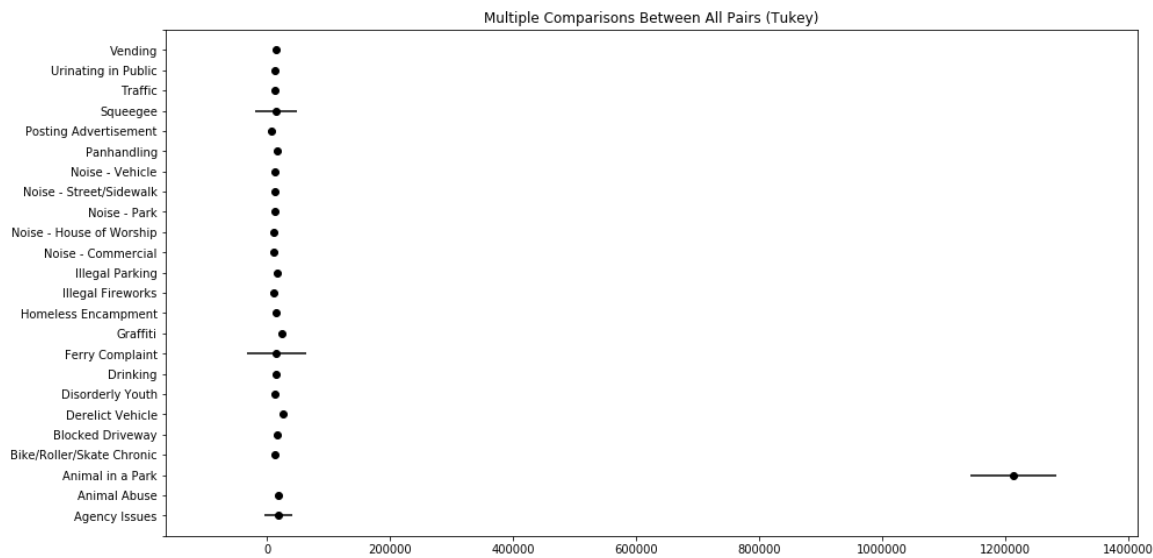
Homeless Encampment	Traffic	-3141.1855	-4640.8903	-1641.4806	True
Homeless Encampment	Urinating in Public	-2492.0912	-5652.9043	668.7219	False
Homeless Encampment	Vending	-1083.8587	-2668.2967	500.5793	False
Illegal Fireworks	Illegal Parking	5531.3719	-210.6138	11273.3576	False
Illegal Fireworks	Noise - Commercial	1004.9665	-4742.8724	6752.8054	False
Illegal Fireworks	Noise - House of Worship	1284.5619	-4896.0061	7465.13	False
Illegal Fireworks	Noise - Park	2126.6262	-3728.8743	7982.1268	False
Illegal Fireworks	Noise - Street/Sidewalk	2148.6445	-3597.5566	7894.8455	False
Illegal Fireworks	Noise - Vehicle	2455.0416	-3307.0605	8217.1438	False
Illegal Fireworks	Panhandling	5735.5407	-1351.026	12822.1074	False
Illegal Fireworks	Posting Advertisement	-2804.2394	-9224.6151	3616.1363	False
Illegal Fireworks	Squeegee	4446.7674	-33605.9626	42499.4975	False
Illegal Fireworks	Traffic	2196.7165	-3634.0881	8027.5211	False
Illegal Fireworks	Urinating in Public	2845.8107	-3614.8322	9306.4537	False
Illegal Fireworks	Vending	4254.0432	-1599.1278	10107.2143	False
Illegal Parking	Noise - Commercial	-4526.4054	-4961.6099	-4091.2008	True
Illegal Parking	Noise - House of Worship	-4246.81	-6560.0701	-1933.5499	True
Illegal Parking	Noise - Park	-3404.7457	-4604.1779	-2205.3134	True
Illegal Parking	Noise - Street/Sidewalk	-3382.7274	-3795.7382	-2969.7167	True
Illegal Parking	Noise - Vehicle	-3076.3303	-3670.9498	-2481.7107	True
Illegal Parking	Panhandling	204.1688	-3963.7058	4372.0434	False
Illegal Parking	Posting Advertisement	-8335.6113	-11229.2206	-5442.0019	True
Illegal Parking	Squeegee	-1084.6044	-38703.2436	36534.0347	False
Illegal Parking	Traffic	-3334.6554	-4407.0515	-2262.2593	True
Illegal Parking	Urinating in Public	-2685.5612	-5667.4496	296.3272	False
Illegal Parking	Vending	-1277.3287	-2465.3365	-89.3209	True
Noise - Commercial	Noise - House of Worship	279.5954	-2048.1556	2607.3464	False
Noise - Commercial	Noise - Park	1121.6597	-105.4874	2348.8068	False
Noise - Commercial	Noise - Street/Sidewalk	1143.678	655.9996	1631.3563	True
Noise - Commercial	Noise - Vehicle	1450.0751	801.3651	2098.7852	True
Noise - Commercial	Panhandling	4730.5742	554.6394	8906.5089	True
Noise - Commercial	Posting Advertisement	-3809.2059	-6714.4129	-903.999	True
Noise - Commercial	Squeegee	3441.8009	-34177.7321	41061.334	False

Noise - Commercial	Traffic	1191.75	88.4433	2295.0567	True
Noise - Commercial	Urinating in Public	1840.8442	-1152.2997	4833.9882	False
Noise - Commercial	Vending	3249.0767	2033.0937	4465.0598	True
Noise - House of Worship	Noise - Park	842.0643	-1740.1168	3424.2454	False
Noise - House of Worship	Noise - Street/Sidewalk	864.0825	-1459.6213	3187.7864	False
Noise - House of Worship	Noise - Vehicle	1170.4797	-1192.2717	3533.2311	False
Noise - House of Worship	Panhandling	4450.9788	-302.988	9204.9455	False
Noise - House of Worship	Posting Advertisement	-4088.8013	-7776.8898	-400.7128	True
Noise - House of Worship	Squeegee	3162.2055	-34525.87	40850.281	False
Noise - House of Worship	Traffic	912.1546	-1613.5246	3437.8337	False
Noise - House of Worship	Urinating in Public	1561.2488	-2196.5005	5318.9981	False
Noise - House of Worship	Vending	2969.4813	392.587	5546.3756	True
Noise - Park	Noise - Street/Sidewalk	22.0183	-1197.4344	1241.4709	False
Noise - Park	Noise - Vehicle	328.4154	-963.8924	1620.7232	False
Noise - Park	Panhandling	3608.9145	-714.0088	7931.8377	False
Noise - Park	Posting Advertisement	-4930.8656	-8043.6557	-1818.0755	True
Noise - Park	Squeegee	2320.1412	-35315.9917	39956.2741	False
Noise - Park	Traffic	70.0903	-1500.4257	1640.6062	False
Noise - Park	Urinating in Public	719.1845	-2475.8343	3914.2034	False
Noise - Park	Vending	2127.417	475.7967	3779.0373	True
Noise - Street/Sidewalk	Noise - Vehicle	306.3972	-327.6372	940.4315	False
Noise - Street/Sidewalk	Panhandling	3586.8962	-586.7839	7760.5763	False
Noise - Street/Sidewalk	Posting Advertisement	-4952.8839	-7854.8491	-2050.9186	True
Noise - Street/Sidewalk	Squeegee	2298.123	-35321.1599	39917.4058	False
Noise - Street/Sidewalk	Traffic	48.072	-1046.6702	1142.8142	False
Noise - Street/Sidewalk	Urinating in Public	697.1663	-2292.8313	3687.1638	False
Noise - Street/Sidewalk	Vending	2105.3988	897.1812	3313.6163	True
Noise - Vehicle	Panhandling	3280.499	-915.0463	7476.0443	False
Noise - Vehicle	Posting Advertisement	-5259.281	-8192.6063	-2325.9558	True
Noise - Vehicle	Squeegee	1991.7258	-35629.9891	39613.4407	False

Noise - Vehicle	Traffic	-258.3252	-1433.6783	917.028	False
Noise - Vehicle	Urinating in Public	390.7691	-2629.6746	3411.2128	False
Noise - Vehicle	Vending	1799.0016	517.2901	3080.713	True
Panhandling	Posting Advertisement	-8539.7801	-13601.5982	-3477.9619	True
Panhandling	Squeegee	-1288.7732	-39135.9798	36558.4333	False
Panhandling	Traffic	-3538.8242	-7828.2369	750.5885	False
Panhandling	Urinating in Public	-2889.7299	-8002.5263	2223.0664	False
Panhandling	Vending	-1481.4975	-5801.2649	2838.2699	False
Posting Advertisement	Squeegee	7251.0068	-30477.137	44979.1507	False
Posting Advertisement	Traffic	5000.9559	1934.874	8067.0377	True
Posting Advertisement	Urinating in Public	5650.0501	1509.702	9790.3983	True
Posting Advertisement	Vending	7058.2826	3949.8768	10166.6885	True
Squeegee	Traffic	-2250.051	-39882.3495	35382.2476	False
Squeegee	Urinating in Public	-1600.9567	-39335.9739	36134.0605	False
Squeegee	Vending	-192.7242	-37828.4948	37443.0463	False
Traffic	Urinating in Public	649.0943	-2500.436	3798.6246	False
Traffic	Vending	2057.3267	495.5184	3619.135	True
Urinating in Public	Vending	1408.2325	-1782.5151	4598.9801	False

In [40]:

```
# Plot show the variance of the complaint type is similar with respective to Request closing time
tukey.plot_simultaneous(figsize = (15,8))
plt.show()
```



By tukey method show the null hypothesis is accepted as there is similar average request closing time to the Complaint type

#Is the type of complaint or service requested and location related?

Null Hypothesis : The type of Complaint or service requested are related to the location.

Alternate Hypothesis : The type of Complaint or service requested are not related to the location.

In [41]:

```
contingency_table = pd.crosstab(data.Complaint_Type,data.Location_Type)
contingency_table
```

Out[41]:

Location_Type	Bridge	Club/Bar/Restaurant	Commercial	Ferry	Highway	House and Store	House of Worship
Complaint_Type							
Animal Abuse	0	0	108	0	0	245	0
Animal in a Park	0	0	0	0	0	0	0
Bike/Roller/Skate Chronic	0	0	0	0	0	0	0
Blocked Driveway	0	0	0	0	0	0	0
Derelict Vehicle	0	0	0	0	19	0	0
Disorderly Youth	0	0	0	0	0	0	0
Drinking	0	458	0	0	0	0	0
Ferry Complaint	0	0	0	1	0	0	0
Graffiti	0	0	0	0	0	0	0
Homeless Encampment	2	0	0	0	19	0	0
Illegal Fireworks	0	0	0	0	0	0	0
Illegal Parking	0	0	0	0	0	0	0
Noise - Commercial	0	21044	0	0	0	0	0
Noise - House of Worship	0	0	0	0	0	0	1068
Noise - Park	0	0	0	0	0	0	0
Noise - Street/Sidewalk	0	0	0	0	0	0	0
Noise - Vehicle	0	0	0	0	0	0	0
Panhandling	0	0	0	0	0	0	0
Posting Advertisement	0	0	0	0	0	0	0
Squeegee	0	0	0	0	0	0	0
Traffic	0	0	0	0	227	0	0
Urinating in Public	0	25	0	0	0	0	0
Vending	0	0	0	0	0	0	0

In [42]:

```
import pandas as pd
import scipy.stats as stats
from math import sqrt
```

In [43]:

```
print(stats.chi2_contingency(contingency_table))
```

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```

In [44]:

```
chi_square , p_value, degrees_of_freedom, expected_frequencies = stats.chi2_contingency(contingency_table)
```

In [45]:

```
chi_square, p_value
```

Out[45]:

```
(2000239.4074142207, 0.0)
```

In [46]:

```
chi_square
```

Out[46]:

```
2000239.4074142207
```

In [47]:

```
p_value
```

Out[47]:

```
0.0
```

In [48]:

```
degrees_of_freedom
```

Out[48]:

```
374
```

In [49]:

```
expected_frequencies
```

Out[49]:

```
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Here from the above observation we state that null hypothesis is accepted as there is relation between complaint type and location