

Customer_Service_Request-2

November 21, 2023

```
[1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

```
[2]: # 1. Import a 311 NYC service request.
df = pd.read_csv('311_Service_Requests_2.csv', low_memory=False)
```

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

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

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

```
      Descriptor      Location Type      Incident Zip \
0    Loud Music/Party  Street/Sidewalk      10034.0
1         No Access  Street/Sidewalk      11105.0
2         No Access  Street/Sidewalk      10458.0
3  Commercial Overnight Parking  Street/Sidewalk      10461.0
4    Blocked Sidewalk  Street/Sidewalk      11373.0
```

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

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

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

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

[5 rows x 53 columns]

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

```
[5]: (255717, 53)
```

```
[6]: 2. #Read or convert the columns 'Created Date' and 'Closed Date' to datetime
      ↪ datatype and
      #create a new column 'Request_Closing_Time' as the time elapsed between
      ↪ request creation and request closing.
      #(Hint: Explore the package/module datetime)
      # Convert 'Created Date' and 'Closed Date' to datetime
      df['Created Date'] = pd.to_datetime(df['Created Date'])
      df['Closed Date'] = pd.to_datetime(df['Closed Date'])

      # Calculate the time difference using the datetime module
      df['Request_Closing_Time'] = df['Closed Date'] - df['Created Date']

      # Display the updated DataFrame
      print(df.head())
```

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

	Agency Name	Complaint Type	\
0	New York City Police Department	Noise - Street/Sidewalk	
1	New York City Police Department	Blocked Driveway	
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	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 Direction	Road Ramp	\
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

	Bridge Highway Segment	Garage Lot Name	Ferry Direction	Ferry Terminal Name	\
0	NaN	NaN	NaN	NaN	
1	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	

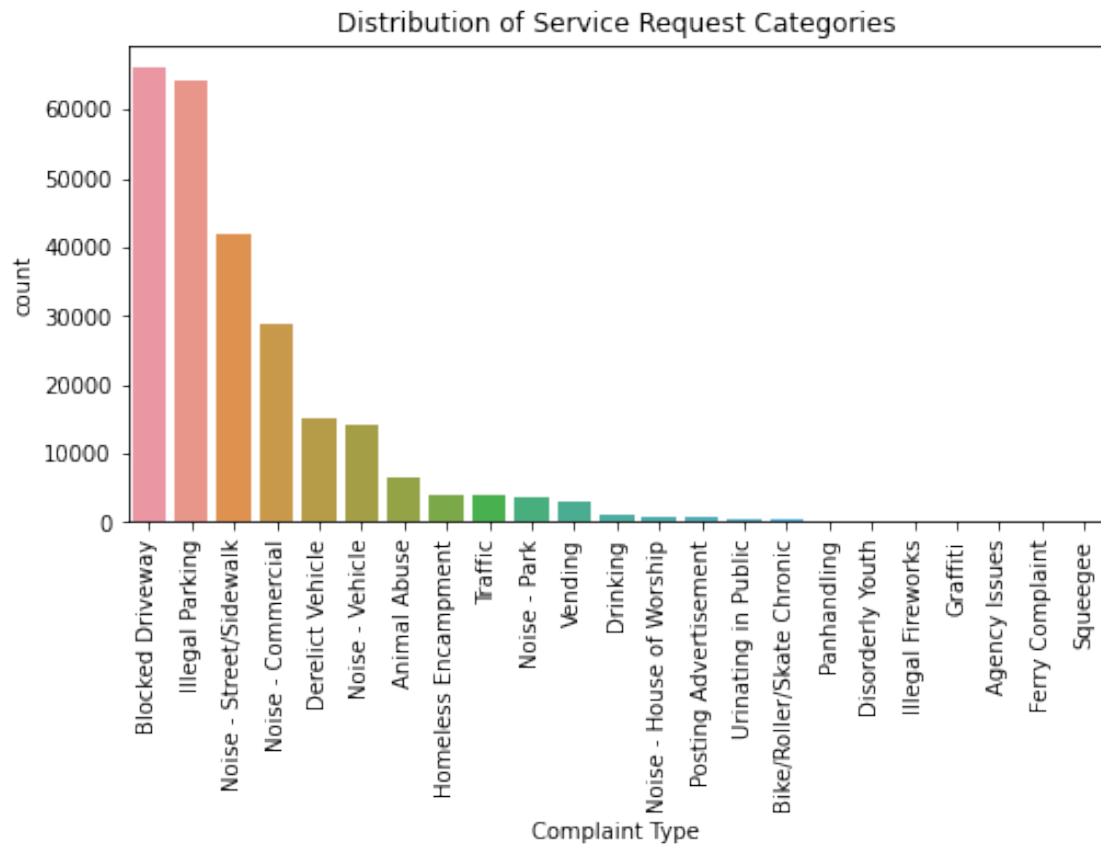
3	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN

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

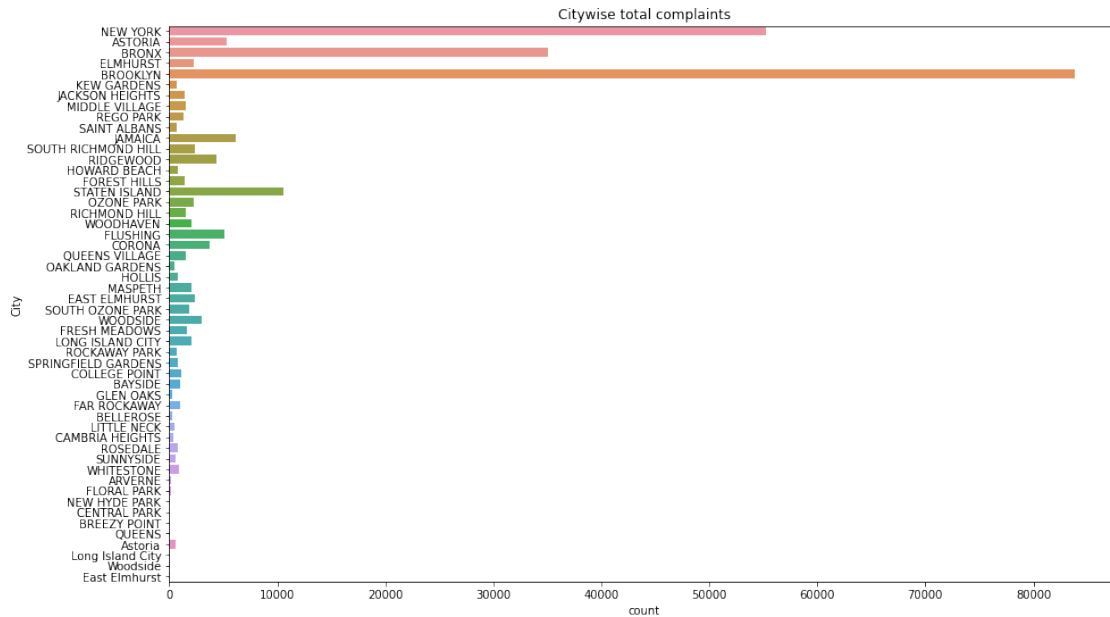
	Request_Closing_Time
0	0 days 00:55:15
1	0 days 01:26:16
2	0 days 04:51:31
3	0 days 07:45:14
4	0 days 03:27:02

[5 rows x 54 columns]

```
[7]: # 3.Provide major insights/patterns that you can offer in a visual format
      ↪(graphs or tables);
      # at least 4 major conclusions that you can come up with after generic data
      ↪mining.
      # Plotting the distribution of service request categories
      plt.figure(figsize=(8, 4))
      sns.countplot(x='Complaint Type', data=df, order=df['Complaint Type'].
      ↪value_counts().index)
      plt.xticks(rotation=90)
      plt.title('Distribution of Service Request Categories')
      plt.show()
```



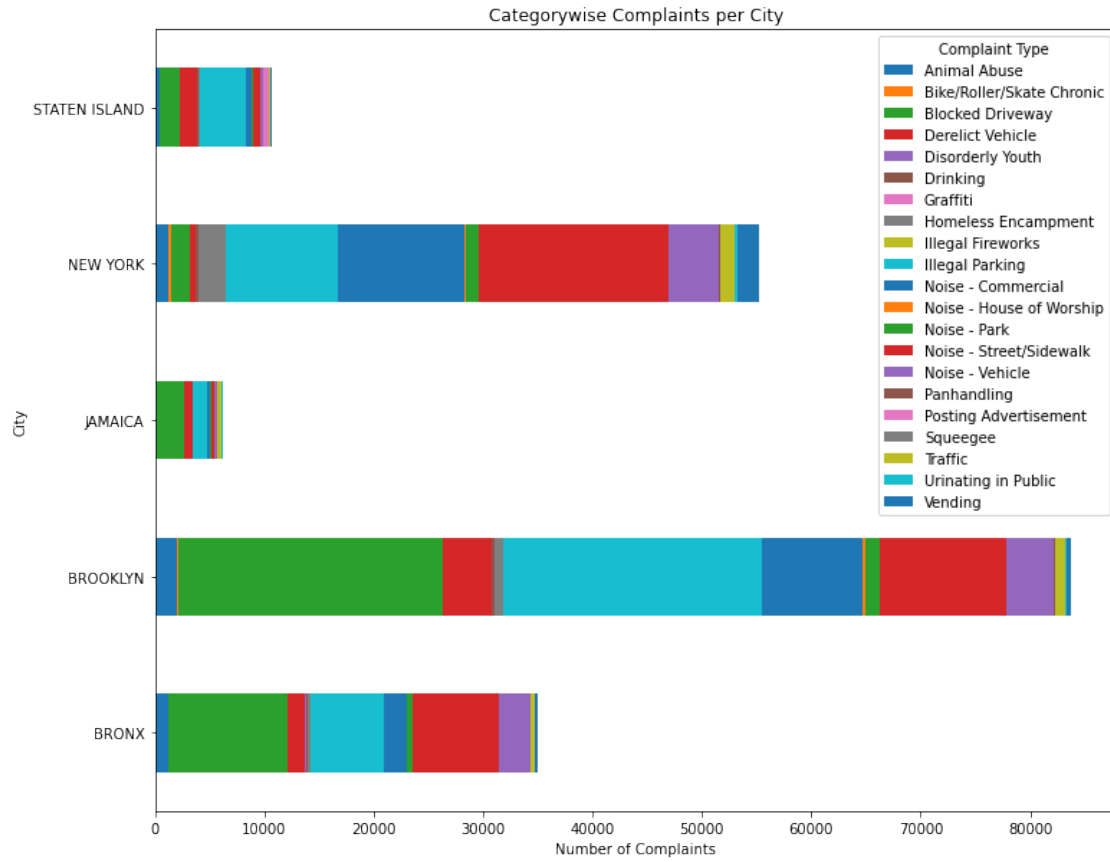
```
[8]: #citywise complaint counts(total)
plt.figure(figsize=(15,9))
plt.title('Citywise total complaints')
sns.countplot(y='City',data=df)
plt.show()
```



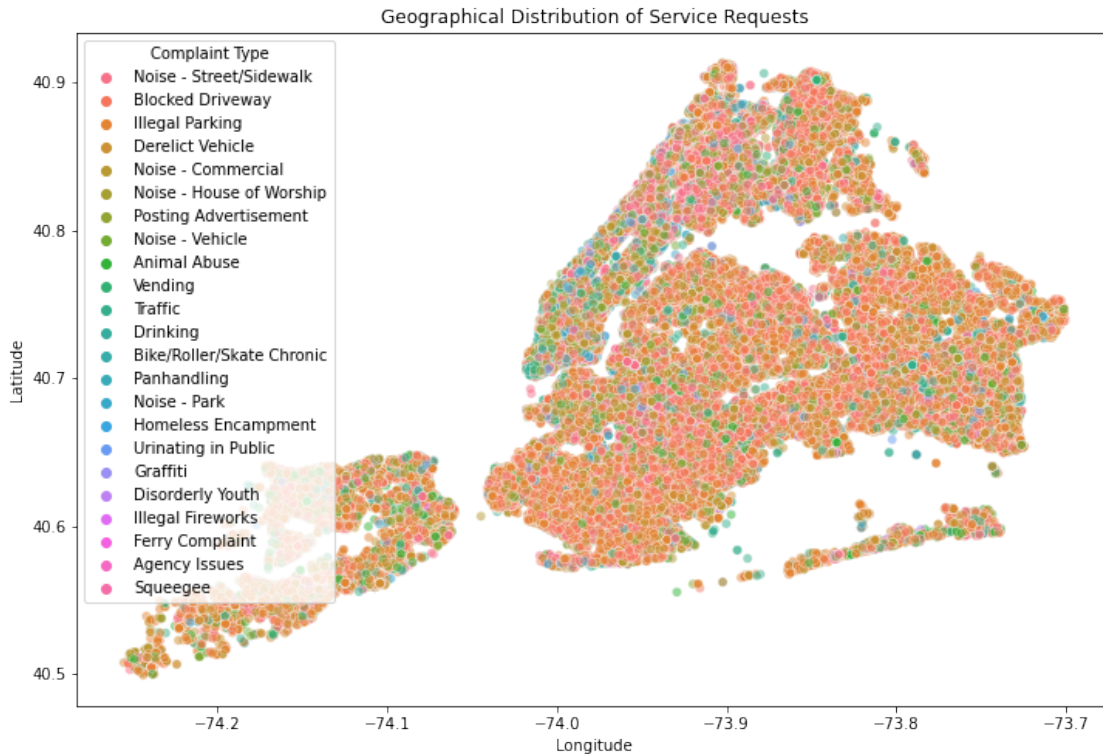
```
[14]: top5cities = df['City'].value_counts().head(5).index.to_list()
      dstop5 = df[df['City'].isin(top5cities)]

      # Citywise complaint counts (typewise)
      df1 = pd.crosstab(dstop5['City'], dstop5['Complaint Type'])

      # Plotting citywise complaint counts (typewise)
      df1.plot(kind='barh', stacked=True, figsize=(12, 10))
      plt.title('Categorywise Complaints per City')
      plt.xlabel('Number of Complaints')
      plt.ylabel('City')
      plt.show()
```



```
[15]: # Assuming 'Latitude' and 'Longitude' are columns in the dataset
plt.figure(figsize=(12, 8))
sns.scatterplot(x='Longitude', y='Latitude', hue='Complaint Type', data=df,
               alpha=0.5)
plt.title('Geographical Distribution of Service Requests')
plt.show()
```



```
[19]: # 4. Order the complaint types based on the average 'Request_Closing_Time',
# grouping them for different locations.

# Assuming 'Created Date' and 'Closed Date' are columns in the dataset
df['Created Date'] = pd.to_datetime(df['Created Date'])
df['Closed Date'] = pd.to_datetime(df['Closed Date'])

# Calculate the 'Request_Closing_Time' for each row
df['Request_Closing_Time'] = (df['Closed Date'] - df['Created Date']).dt.
    total_seconds() / 3600

# Group by 'City' and 'Complaint Type', calculate the average
    'Request_Closing_Time'
grouped_df = df.groupby(['City', 'Complaint Type'])['Request_Closing_Time'].
    mean().reset_index()

# Order the complaint types based on average closing time within each city
ordered_complaints = grouped_df.groupby('City').apply(lambda x: x.
    sort_values('Request_Closing_Time')).reset_index(drop=True)

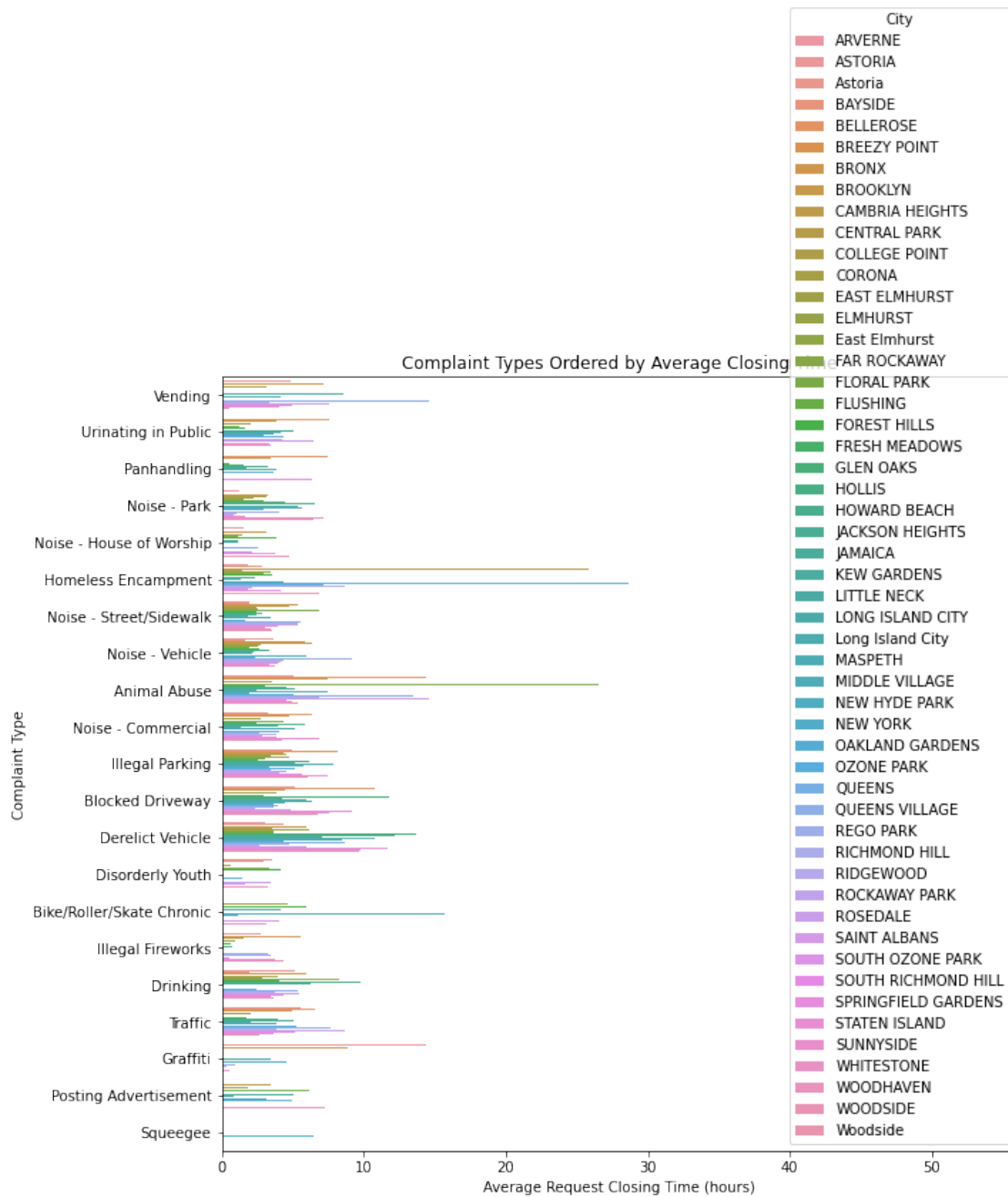
# Plotting the ordered complaint types based on average closing time
plt.figure(figsize=(10, 10))
```



```

sns.barplot(x='Request_Closing_Time', y='Complaint Type', hue='City',
            data=ordered_complaints)
plt.title('Complaint Types Ordered by Average Closing Time')
plt.xlabel('Average Request Closing Time (hours)')
plt.ylabel('Complaint Type')
plt.show()

```



```
[ ]: # 5.Perform a 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 is similar or not
↳(overall)
Are the type of complaint or service requested and location related?
```

```
[21]: import scipy.stats as stats

# Assuming 'Request_Closing_Time' is the column representing response time
complaint_types = df['Complaint Type'].unique()

# Create a list to store complaint types with non-missing and non-infinite
↳response times
valid_data = []

# Filter and clean the data
for complaint_type in complaint_types:
    subset = df[df['Complaint Type'] == complaint_type]['Request_Closing_Time']
    subset = subset.replace([np.inf, -np.inf], np.nan).dropna()

    if not subset.empty:
        valid_data.append(subset)

# Perform one-way ANOVA
statistic, p_value = stats.f_oneway(*valid_data)

# Check the p-value
alpha = 0.05
if p_value < alpha:
    print(f'Reject the Null Hypothesis. Average response time across complaint
↳types is not similar (p-value: {p_value})')
else:
    print(f'Fail to reject the Null Hypothesis. Average response time across
↳complaint types is similar (p-value: {p_value})')
```

Reject the Null Hypothesis. Average response time across complaint types is not similar (p-value: 0.0)

```
[22]: # Assuming 'Complaint Type' and 'Location' are the relevant columns
contingency_table = pd.crosstab(df['Complaint Type'], df['Location'])

# Perform Chi-Square Test
chi2_stat, p_value, dof, expected = stats.chi2_contingency(contingency_table)
```

```

# Check the p-value
alpha = 0.05
if p_value < alpha:
    print(f'Reject the Null Hypothesis. There is a relationship between the
    ↳type of complaint/service and location (p-value: {p_value})')
else:
    print(f'Fail to reject the Null Hypothesis. There is no relationship
    ↳between the type of complaint/service and location (p-value: {p_value})')

```

Reject the Null Hypothesis. There is a relationship between the type of complaint/service and location (p-value: 0.0)

[]: In practical terms, this means that the distribution of complaint types **is not** independent of the location, **and** there **is** an association between the **type** of complaint/service **and** the location where the complaint/service **is** requested.