In [1]:

```
import os
```

In [7]:

```
cwd = os.chdir(r'C:\Machine_learning_datafiles\simplilearn_projects\nyc_service_request')
os.getcwd()
```

Out[7]:

```
'C:\\Machine_learning_datafiles\\simplilearn_projects'
```

In [8]:

```
dataset= '311_Service_Requests_from_2010_to_Present.csv'
```

In [9]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import scipy
plt.style.use('ggplot')
```

In [10]:

```
pd.set_option('max_columns',5000)
```

In [11]:

```
import warnings
warnings.filterwarnings('ignore')
```

In [12]:

```
data = pd.read_csv(dataset)
```

In [13]:

```
data['Closed Date'] = data['Closed Date'].astype('datetime64',)
data['Created Date']= data['Created Date'].astype('datetime64')
data['Due Date'] = pd.to_datetime(data['Due Date'], unit='ns')
data['Resolution Action Updated Date'] = pd.to_datetime(data['Resolution Action Updated
Date'], unit='ns')
```

In [14]:

```
data.to_csv('modified_311_Service_Requests.csv',index=False)
```

In [15]:

```
data = pd.read_csv('modified_311_Service_Requests.csv', parse_dates=['Created Date','Clos
ed Date','Due Date',\
                                                                     'Resolution Action
Updated Date'])
```

In [16]:

```
print('The dataset has {:,d} rows and {} columns'.format(data.shape[0],data.shape[1]))
```

```
The dataset has 364,558 rows and 53 columns
```

In [17]:

```
data.isnull().any().sum()
```

Out[17]:

35

In [18]:

```
cols_to_drop = ['School Name','School Number','School Region','School Code','School Phon
e Number',\
                'School Address','School City','School State','School Zip','School or Ci
tywide Complaint',\
                'Vehicle Type','Taxi Company Borough','Taxi Pick Up Location','Bridge Hi
ghway Name',\
                'Bridge Highway Direction','Road Ramp','Bridge Highway Segment','Garage
Lot Name',\
                'Ferry Direction','Ferry Terminal Name']
```

In [19]:

```
#dropping null columns
data.drop(axis=1,labels=cols_to_drop,inplace=True)
```

In [20]:

```
data.head(2)
```

Out[20]:

	Unique Key	Created Date	Closed Date	Agency	Agency Name	Complaint Type	Descriptor	Location Type	Incident Zip	Incident Address	
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	Street/Sidewalk	10034.0	71 VERMILYEA AVENUE	VE
1	32309934	2015-12-31 23:59:44	2016-01-01 01:26:57	NYPD	New York City Police Department	Blocked Driveway	No Access	Street/Sidewalk	11105.0	27-07 23 AVENUE	2

In [21]:

```
data['Created Date'].isnull().sum()
```

Out[21]:

0

In [22]:

```
data['Closed Date'].isnull().sum()
```

Out[22]:

2381

The closed date has rows with missing values so we will drop those rows

In [23]:

```
data.dropna(subset=['Closed Date'], inplace=True) #dropping NaN values of closed date
```

In [24]:

```
print('The dataset when the null values have been removed has {:,d} rows and {} columns'.
format(data.shape[0],data.shape[1]))
```

The dataset when the null values have been removed has 362,177 rows and 33 columns

In [25]:

```
#finding the request closing time ie difference btw created and closing dates, and conver
ting to string to enable us use \
#regular expressions

data['Request Closing Time'] = (data['Closed Date'].dt.date - data['Created Date'].dt.da
te).astype('str')
```

In [26]:

```
import re
pattern = re.compile(r'\w+') #to match digits
```

In [27]:

```
#regular expressions to extract numbers and converting them to integers
data['Request Closing Time']= data['Request Closing Time'].apply(lambda x: re.match(patte
rn,x).group(0)).astype(int)
```

data.info()

In [34]:

```
#Mean Request closing Time by City
request_closing_time_by_complaint_type =\
data.groupby(['Complaint Type'])[['Request Closing Time']].mean().sort_values(by='Reques
t Closing Time')[:10].reset_index()
```

In [76]:

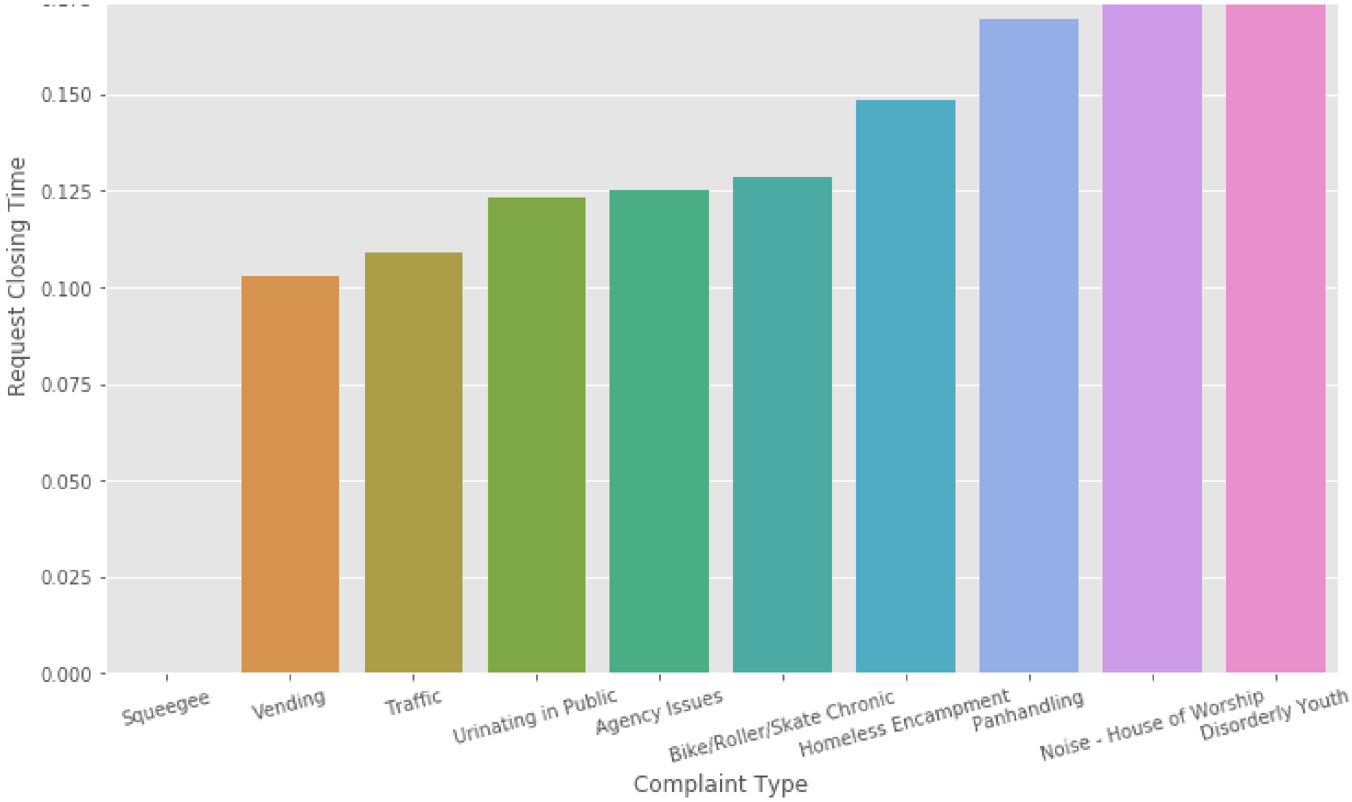
```
request_closing_time_by_complaint_type
```

Out[76]:

	Complaint Type	Request Closing Time
0	Squeegee	0.000000
1	Vending	0.102748
2	Traffic	0.109122
3	Urinating in Public	0.123245
4	Agency Issues	0.125000
5	Bike/Roller/Skate Chronic	0.128421
6	Homeless Encampment	0.148596
7	Panhandling	0.169231
8	Noise - House of Worship	0.191011
9	Disorderly Youth	0.196825

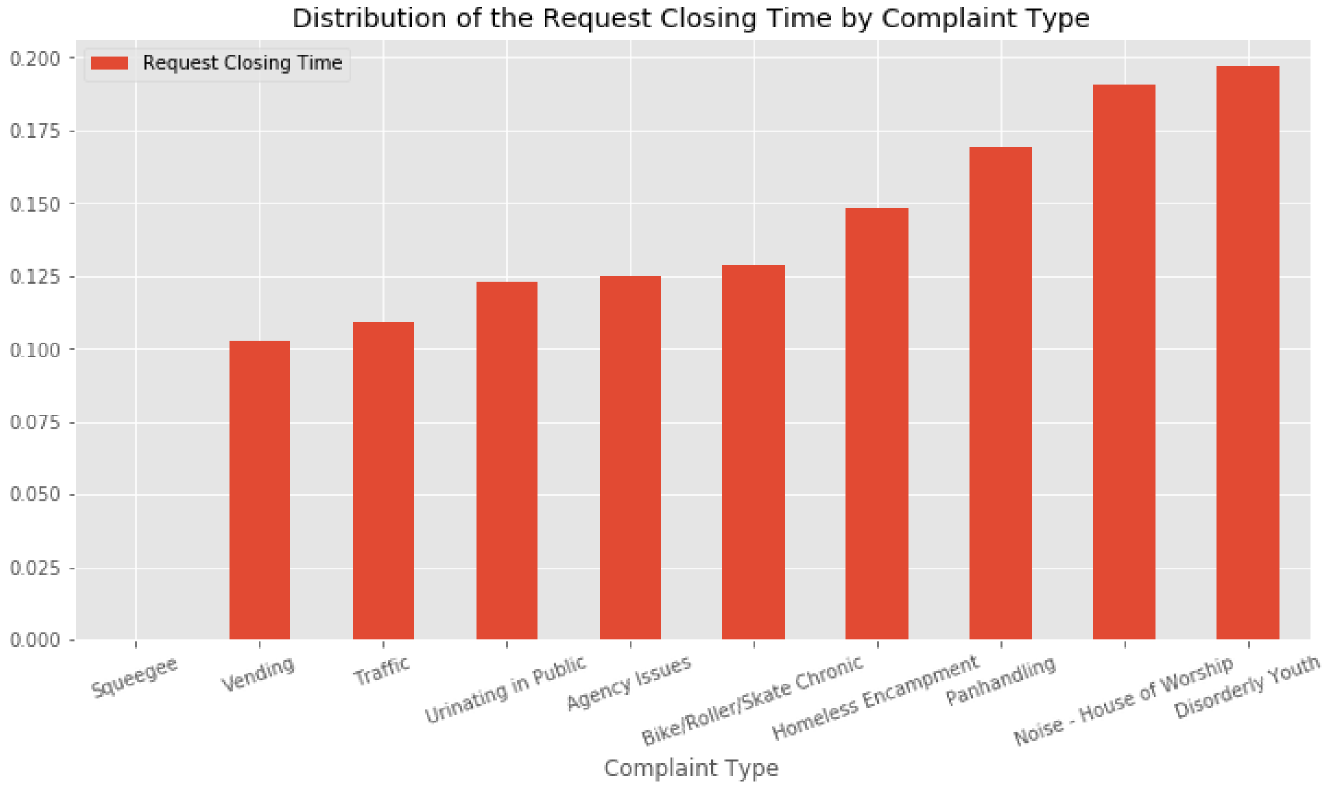
In [93]:

```
plt.figure(figsize=[12,8])
sns.barplot('Complaint Type', 'Request Closing Time', data=request_closing_time_by_compla
int_type)
plt.xticks(rotation=15)
plt.title('Distribution of the Request Closing Time by Complaint Type (Top 10 with the le
ast closing request time)');
plt.savefig('Request_closing_time_by_complaint_type.jpeg',papertype='a3')
```



In [79]:

```
fig,ax=plt.subplots(figsize=[12,6])
request_closing_time_by_complaint_type.plot(kind='bar',x='Complaint Type',rot=20,ax=ax)
plt.title('Distribution of the Request Closing Time by Complaint Type');
plt.savefig('Request_closing_time_by_complaint_type.png',)
```



The complaint type with the fastest mean response time is Squeegee

In [275]:

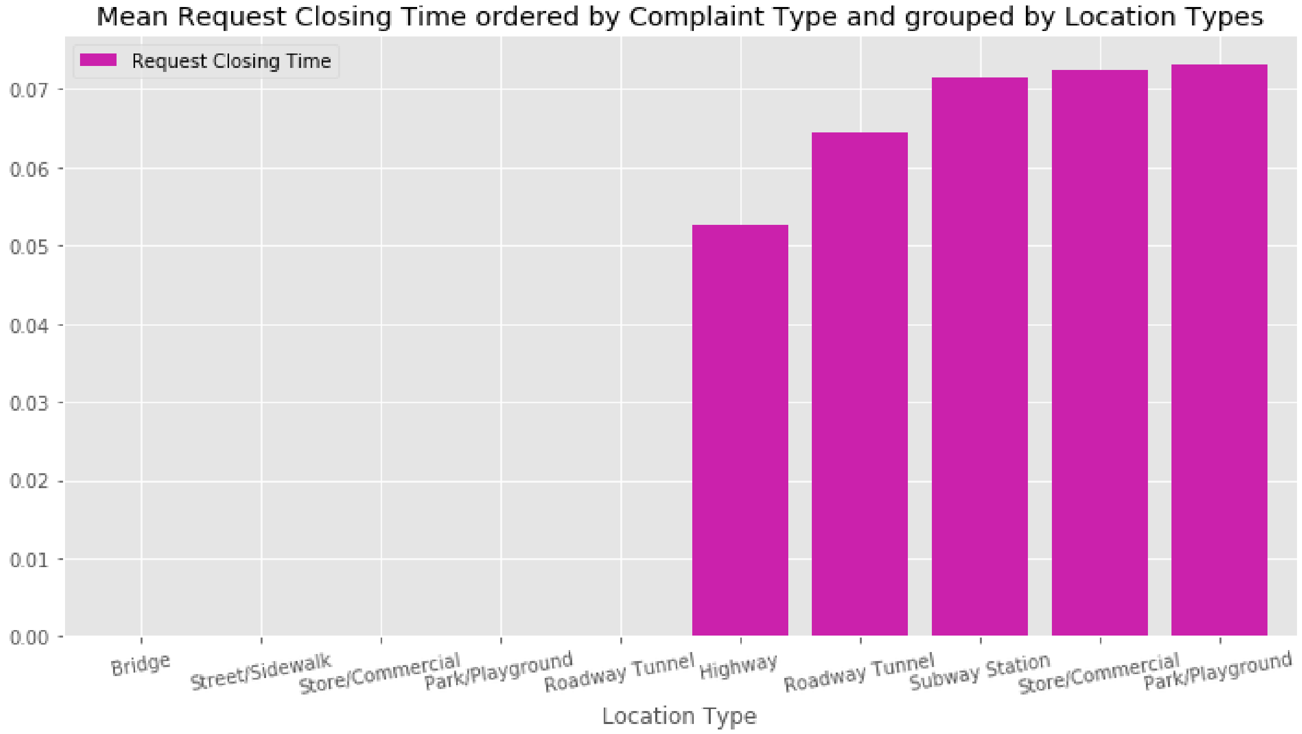
```
#Mean Request closing time for complaint type grouped by location type
mean_request_closing_time_per_location_type = \
data.groupby(['Location Type','Complaint Type'])[['Request Closing Time']].mean().\
sort_values(by='Request Closing Time').reset_index()
```

In [282]:

```
mean_request_closing_time_per_location_type[:10].to_csv('mean_request_closing_time_per_lo
cation_type.csv')
request_closing_time_by_complaint_type.to_csv('request_closing_time_by_complaint_type.csv
')
```

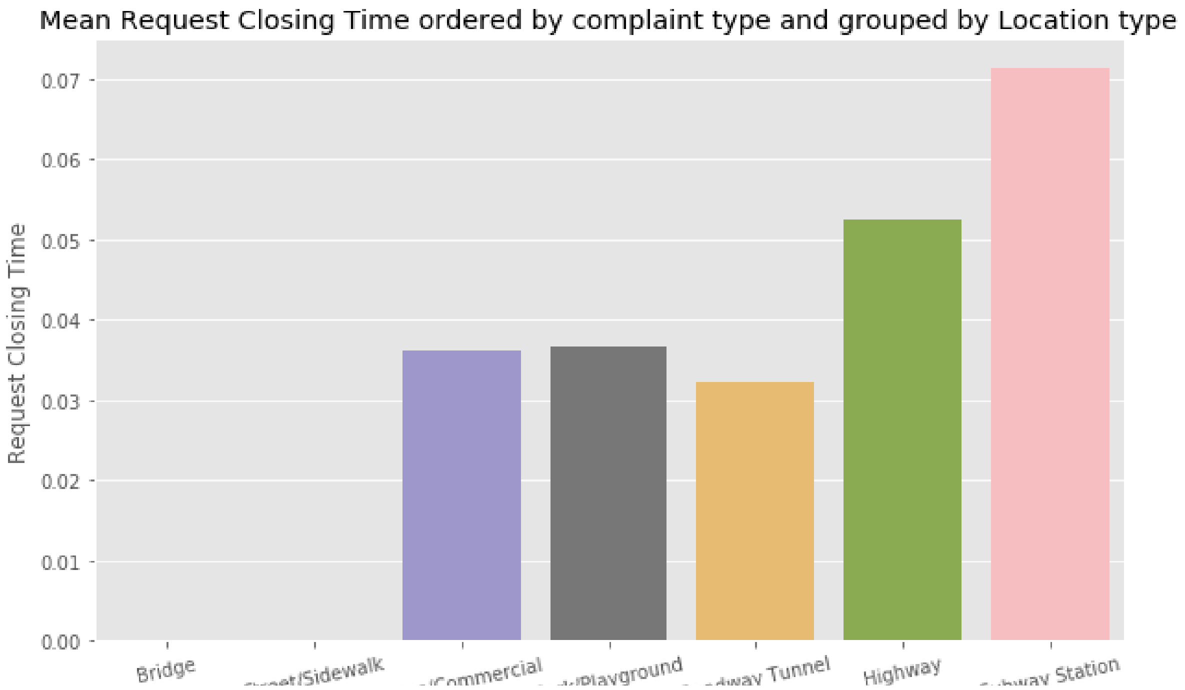
In [289]:

```
fig,ax= plt.subplots(figsize=[12,6])
mean_request_closing_time_per_location_type[:10].plot.bar(x='Location Type',rot=10,ax=ax
,width=0.80,color='#cb21ac')
plt.title('Mean Request Closing Time ordered by Complaint Type and grouped by Location Ty
pes')
plt.savefig('top10_mean_request_closing_time_per_location_type.jpg');
```



In [271]:

```
plt.figure(figsize=[10,6])
sns.barplot(x='Location Type', y= 'Request Closing Time',data=mean_request_closing_time_p
er_location_type[:10], ci=False)
plt.xticks(rotation=12)
plt.title('Mean Request Closing Time ordered by complaint type and grouped by Location ty
pe');
```



From the table above we can see that the complaint types with the fastest response are complaints made about a Homeless Encampment around the Bridge, Roadway tunnel, Squeegee in street/sidewalk, panhandling around the park/playground and Posting Advertisement around store/commercials.

In [81]:

```
complaints_by_city = data[['City','Complaint Type']]
```

Total complaint Type by city

In [82]:

```
top_10_complaints_by_city= data.groupby(['City']).agg({'Complaint Type':'count'}\
                                                    ).sort_values(by='Complaint Type',ascendi
ng =False).reset_index()[:10]
```

In [283]:

```
top_10_complaints_by_city.to_csv('top_10_complaints_by_city.csv')
```

In [285]:

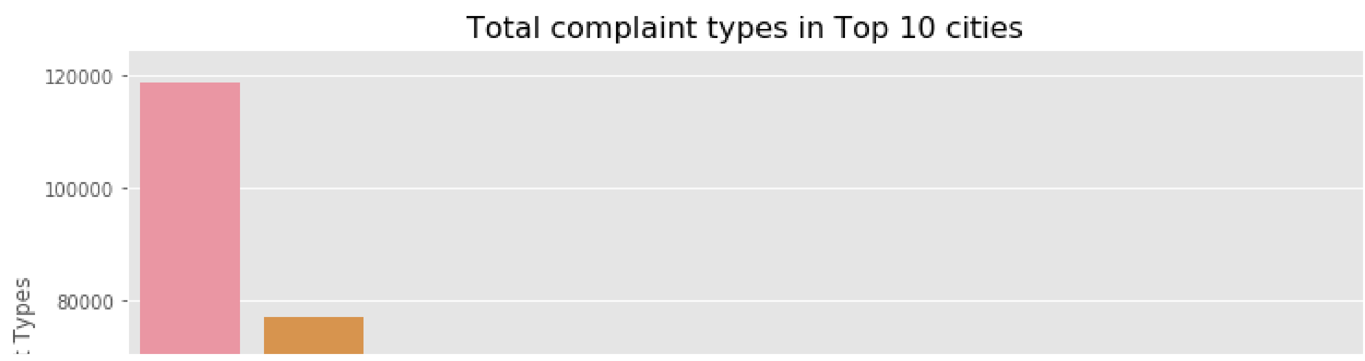
```
top_10_complaints_by_city
```

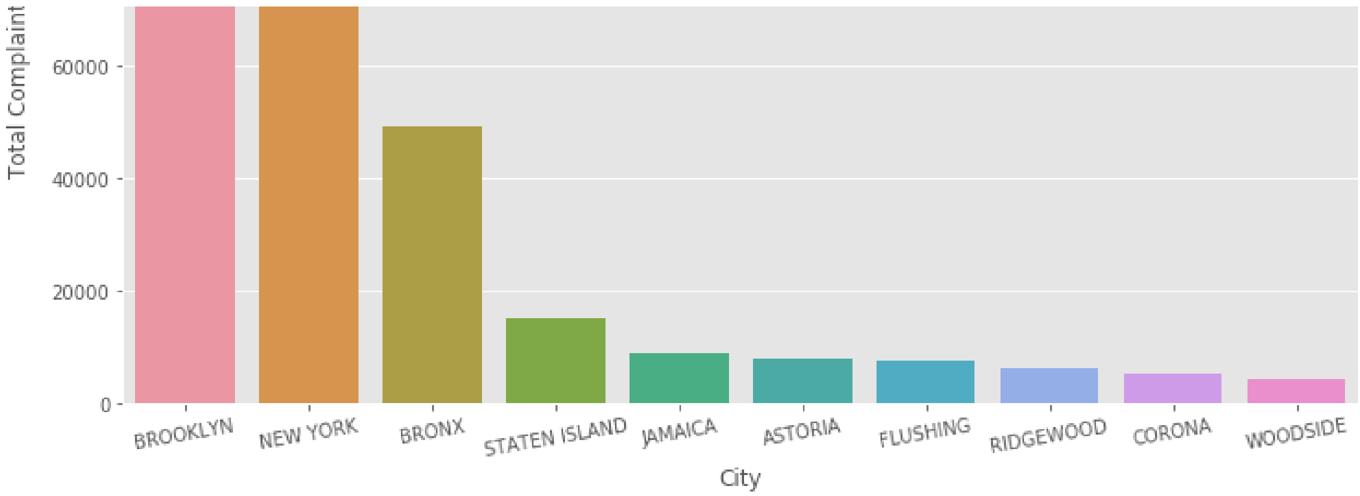
Out[285]:

	City	Complaint Type
0	BROOKLYN	118849
1	NEW YORK	77289
2	BRONX	49166
3	STATEN ISLAND	15335
4	JAMAICA	8930
5	ASTORIA	7991
6	FLUSHING	7486
7	RIDGEWOOD	6391
8	CORONA	5383
9	WOODSIDE	4357

In [286]:

```
plt.figure(figsize=[12,7])
sns.barplot('City', 'Complaint Type', data=top_10_complaints_by_city)
plt.xticks(rotation=10)
plt.title('Total complaint types in Top 10 cities', fontsize=16)
plt.ylabel('Total Complaint Types');
plt.savefig('request_closing_request_time_by_city.jpeg',dpi=100)
```





From the table above we see that the city with the major complaints are made is Brooklyn, followed by New York. With Howard Beach as the least city

In [94]:

```
most_complaint_type = pd.value_counts(data['Complaint Type'])
```

In [292]:

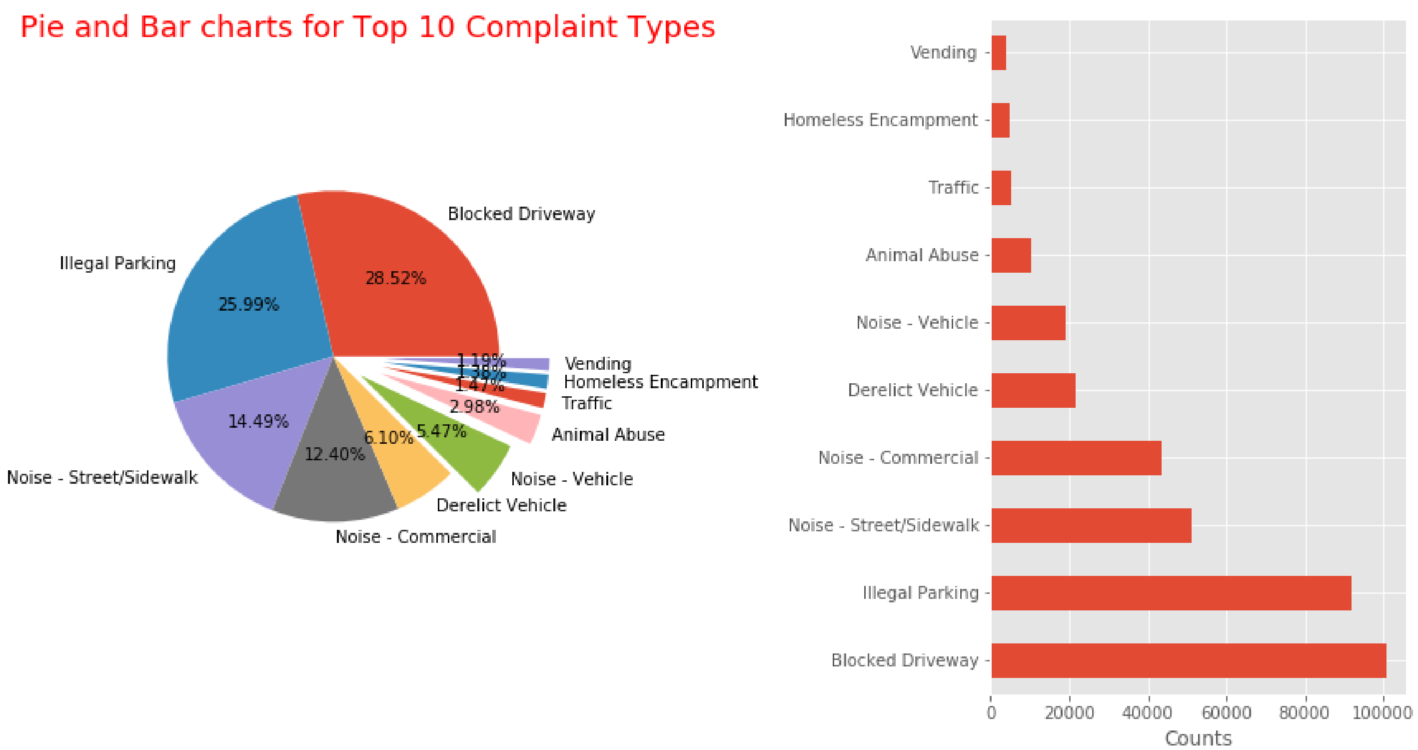
```
most_complaint_type.reset_index().to_csv('most_complaint_type.csv')
```

In [106]:

```
fig,ax = plt.subplots(1,2, figsize=[12,6.5])
fig.suptitle('Pie and Bar charts for Top 10 Complaint Types', fontsize=18, color='red', h
a='right')

most_complaint_type[:10].plot(kind='pie',autopct='%.2f%%',ax=ax[0],explode=(0,0,0,0,0,0.
2,0.3,0.3,0.3,0.3))
ax[0].set(ylabel='')

most_complaint_type[:10].plot.barh(x='Complaint Type',ax=ax[1])
ax[1].set_xlabel('Counts')
plt.tight_layout(1.2)
plt.savefig('Top_10_Complaint_Types.jpeg',dpi=140, papertype='a3');
```



Comment: From the visualisation, we see that the top complaints are complaints involving Blocked Driveways

followed by illegal packing. The least are complaints involving vending machine matters

Complaints status

In [31]:

```
data.Status.value_counts().to_frame()
```

Out[31]:

	Status
Closed	362114
Open	36
Assigned	26
Draft	1

Comment: This tells us that majority of the complaint cases opened were closed.

Counts of Request closing time

In [54]:

```
data['Request Closing Time'].value_counts().to_frame().sort_index()
```

Out[54]:

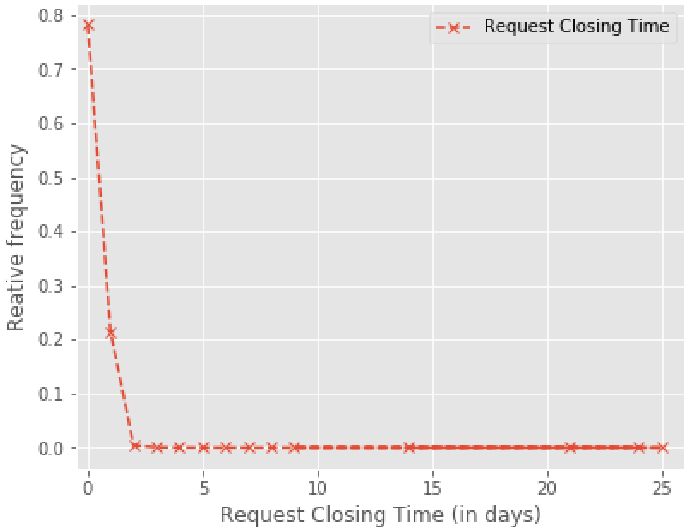
	Request Closing Time
0	283357
1	76864
2	1546
3	259
4	76
5	27
6	25
7	13
8	3
9	2
14	1
21	1
24	1
25	2

In [138]:

```
fig,ax= plt.subplots(1,2,figsize=[14,5])
data['Request Closing Time'].value_counts().to_frame().transform(lambda x:x/x.sum()).plot
(marker='x',ax=ax[0],linestyle='--')
ax[0].set(xlim=(-0.5,26),xlabel= 'Request Closing Time (in days)',ylabel= 'Reative frequ
ency')

data['Request Closing Time'].value_counts().to_frame().sort_index().transform(lambda x:x
/x.sum()).plot(kind='bar',ax=ax[1],rot=0,width=0.9)
ax[1].set(xlabel= 'Request Closing Time (in days)',ylabel= 'Reative frequency',xlim=(-1,
14))
fig.suptitle('Relative Frequency Distribution for Request closing Time (in days)',fontsiz
e=14);
```

Relative Frequency Distribution for Request closing Time (in days)



comment: From the table we see that majority of the complaint cases filed was closed in less than a day

Statistical Testing

Questions:

1. **Is the average response time across complaint types similar or not (overall)**
2. **Are the type of complaint or service requested and location related**

Question 1

We will be using one way ANOVA to test the similarity or difference in mean response time across complaint types (ie if the difference across their means is statstically significant or not.

Firstly, we will state our hypotheses:

<u>**Hypotheses statements**</u>

Null hypothesis: The average response time across complaint types is equal or similar.

Alternative hypothesis: The average response time across complaint types is not equal or is different.

alpha= 0.05

In [139]:

```
from scipy.stats import f_oneway
```

In [140]:

```
unique_complaint_type = data['Complaint Type'].unique().tolist()
```

In [141]:

```
print(unique_complaint_type, end='')
```

```
['Noise - Street/Sidewalk', 'Blocked Driveway', 'Illegal Parking', 'Derelict Vehicle', 'N
oise - Commercial', 'Noise - House of Worship', 'Posting Advertisement', 'Noise - Vehicle
', 'Animal Abuse', 'Vending', 'Traffic', 'Drinking', 'Bike/Roller/Skate Chronic', 'Panhan
dling', 'Noise - Park', 'Homeless Encampment', 'Urinating in Public', 'Graffiti', 'Disord
erly Youth', 'Illegal Fireworks', 'Agency Issues', 'Squeegee', 'Animal in a Park']
```

In order to create arrays for each of the complaint types, i will create a dictionary of complaint types, each with their request closing times as lists, and then convert each of them to arrays.

In [142]:

```
from collections import defaultdict
```

In [143]:

```
complaint_type_dict = defaultdict(list)
```

In [144]:

```
for complaint, closing_time in data[['Complaint Type','Request Closing Time']].values:
    if complaint in unique_complaint_type:
        complaint_type_dict[complaint].append(closing_time)
```

In [145]:

```
len(complaint_type_dict) #same with the number of unique complaint types
```

Out[145]:

```
23
```

In [146]:

```
complaint_type_array = np.array([array for key,array in complaint_type_dict.items()]) #co
nverting each list to array

# or use np.append([],[array for key,array in complaint_type_dict.items()]) #converting e
ach list to array
```

In [147]:

```
noise_street_sidewlak = complaint_type_array[0]
blocked_driveway = complaint_type_array[1]
illegal_parking = complaint_type_array[2]
derelict_vehicle =complaint_type_array[3]
noise_commercial = complaint_type_array[4]
posting_advert = complaint_type_array[5]
noise_vehicle = complaint_type_array[6]
animal_abuse = complaint_type_array[7]
vending = complaint_type_array[8]
traffic = complaint_type_array[9]
drinking = complaint_type_array[10]
bike_roller_skate = complaint_type_array[11]
panhandling = complaint_type_array[12]
noise_park = complaint_type_array[13]
homeless_encamp = complaint_type_array[14]
urinate_pub = complaint_type_array[15]
graffiti = complaint_type_array[16]
disorder_youth = complaint_type_array[17]
illegal_fireworks = complaint_type_array[18]
agency_issues = complaint_type_array[19]
squeegee = complaint_type_array[20]
animal_park = complaint_type_array[21]
```

In [148]:

```
#One way ANOVA to test if the difference in means is statistically significant or not
F_statistic,p_val = \
f_oneway(noise_street_sidewlak,blocked_driveway,illegal_parking,derelict_vehicle,noise_co
mmercial,\
         posting_advert,noise_vehicle,animal_abuse,vending,traffic,drinking,bike_roller_
skate,panhandling,\
         noise_park,homeless_encamp,urinate_pub,graffiti,disorder_youth,illegal_firework
s,agency_issues,\
         squeegee,animal_park)
```

In [149]:

```
print('F-Statistic: {}, p-value:{}'.format(F_statistic,p_val))
```

```
F-Statistic: 132.46529732301363, p-value:0.0
```

F-Statistic: 132.4652973230136З, p-value:0.0

Comment

From the one way ANOVA test, the p-value is far less than the significance level so we will reject the null hypothesis and conclude that the mean request closing time across complaint types is different, overall

Question 2

In testing the relationship between location type and complaint type,we will use the chi square test for independence.

Null hypothesis : There is no relationship/association between location type and complaint type

Alternative Hypothesis: There is a relationship/an association between location type and complaint type

Alpha: 5%

In [150]:

```
from scipy.stats import chi2_contingency
```

In [151]:

```
contingency_table = pd.crosstab(data['Location Type'], data['Complaint Type'])
```

In [152]:

```
chisq_statistic, p_value, ddof, expected = chi2_contingency(contingency_table.values)
```

In [153]:

```
print('Chi square statistic: {}, p-value: {}'.format(chisq_statistic,p_value))
```

```
Chi square statistic: 1625098.2311304228, p-value: 0.0
```

comment:

From the chi square test results, we see that the p-value is less than the alpha or level of significance, hence we will reject our null hypothesis and conclude that there is a relationship between Location Type and Complaint Type

In [163]:

```
with open('Statisctical testing.txt', 'r+') as file:
    f = file.read()
```

In [ ]:

```
```