```
In [1]:
import pandas as pd
import datetime as dt
##1) Import a 311 NYC service request.
df=pd.read csv('311 Service Requests from 2010 to Present.csv',low memory=False)
##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 a
nd request closing
df['Closed Date']=pd.to datetime(df['Closed Date'])
df['Created Date']=pd.to datetime(df['Created Date'])
In [2]:
df['Request_Closing_Time'] = (df['Closed Date'] - df['Created Date']).dt.total_seconds()
In [3]:
df.shape
Out[3]:
(300698, 54)
In [7]:
###Checking the Null values
df.Request Closing Time.isnull().sum()
Out[7]:
2164
In [8]:
####Data Imputation
df=df[df['Request Closing Time'].notnull()]
In [9]:
df.shape
Out[9]:
(298534, 54)
In [20]:
####Provide major insights/patterns that you can offer in a visual format (graphs or tab
les):
#####at least 4 major conclusions that you can come up with after generic data mining.
In [21]:
##A.Complaints based on Location Type
df1=df['Location Type'].value counts()
df1
Out[21]:
Street/Sidewalk
                              247503
Store/Commercial
                               20183
Club/Bar/Restaurant
                               17227
Residential Building/House
                                6953
Park/Playground
                                 4751
House of Worship
                                 927
Residential Building
                                 227
Highway
                                  214
```

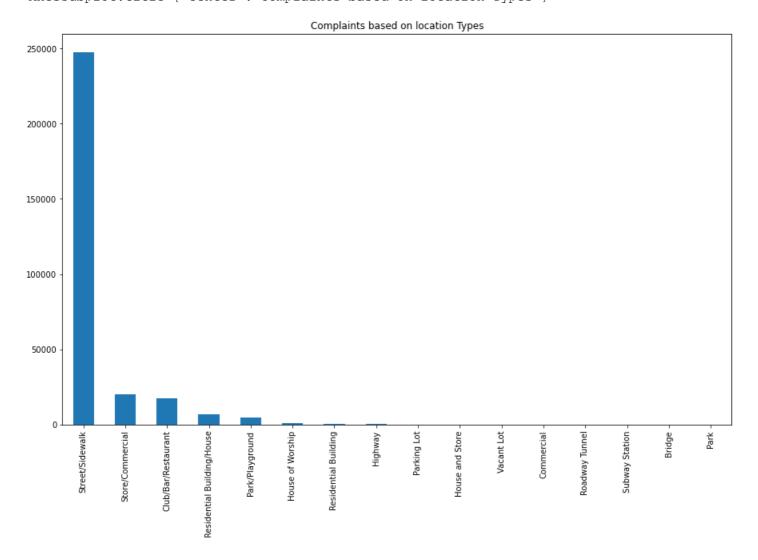
```
Parking Lot
                                   117
House and Store
                                    93
Vacant Lot
                                    77
Commercial
                                    62
Roadway Tunnel
                                    35
                                    34
Subway Station
                                     2
Bridge
Park
Name: Location Type, dtype: int64
```

# In [29]:

```
df1.plot(kind='bar',figsize=(15,9),title='Complaints based on location Types')
```

## Out[29]:

<AxesSubplot:title={'center':'Complaints based on location Types'}>



# In [23]:

```
###Insights on complaints
df2=df['Complaint Type'].value_counts()
df2
```

# Out[23]:

Blocked Driveway	76810
Illegal Parking	74532
Noise - Street/Sidewalk	48076
Noise - Commercial	35247
Derelict Vehicle	17588
Noise - Vehicle	17033
Animal Abuse	7768
Traffic	4496
Homeless Encampment	4416
Noise - Park	4022
Vending	3795
Dainleina	1075

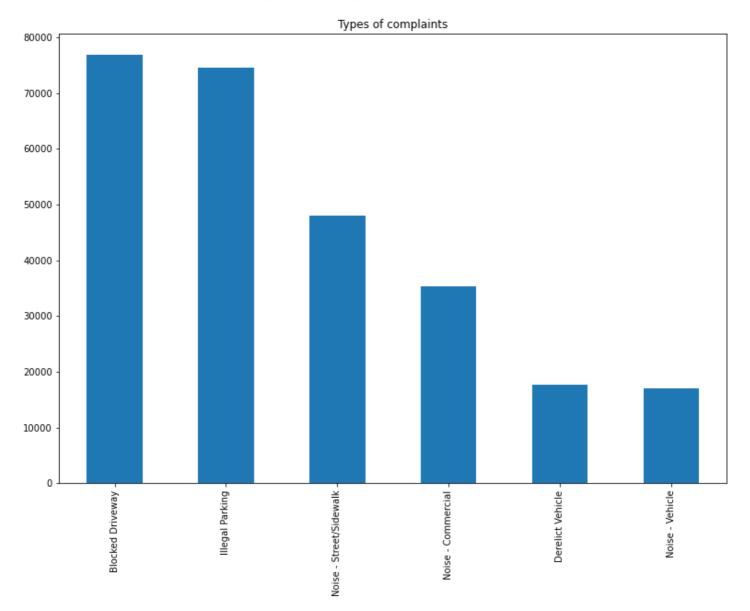
```
הדדוועדווא
                                1213
Noise - House of Worship
                                929
Posting Advertisement
                                 648
Urinating in Public
                                592
                                424
Bike/Roller/Skate Chronic
Panhandling
                                305
                                286
Disorderly Youth
Illegal Fireworks
                                168
                                113
Graffiti
                                   6
Agency Issues
                                   4
Squeegee
                                   1
Animal in a Park
Name: Complaint Type, dtype: int64
```

# In [28]:

```
###Insights on Top 6 complaints
(df['Complaint Type'].value_counts()).head(6).plot(kind='bar',figsize=(13,9),title='Type
s of complaints')
```

#### Out[28]:

<AxesSubplot:title={'center':'Types of complaints'}>



## In [35]:

```
###Analysis based on Complaints from each City
df3=df['City'].value_counts()
df3
```

### Out[35]:

BROOKLYN 98295 NEW YORK 65972

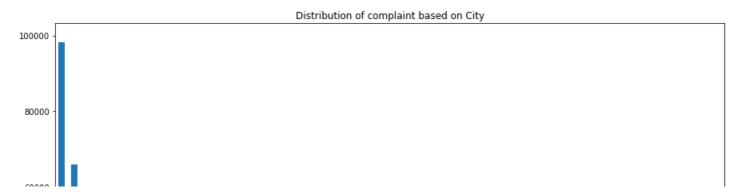
BRONX	40697
STATEN ISLAND	12338
JAMAICA	7294
ASTORIA	6330
FLUSHING	5970
RIDGEWOOD	5162
CORONA	4295
WOODSIDE	3544
SOUTH RICHMOND HILL	
OZONE PARK	2755
EAST ELMHURST	2733
ELMHURST	2673
WOODHAVEN	2463
MASPETH LONG ISLAND CITY SOUTH OZONE PARK	2436
SOUTH OZONE PARK	2173
RICHMOND HILL	1902
FRESH MEADOWS	1899
	1814
MIDDLE VILLAGE	1765
	1688
FOREST HILLS	1688
REGO PARK	1486
BAYSIDE	1221
COLLEGE POINT	1220
FAR ROCKAWAY	1179
WHITESTONE	1098
HOLLIS	1012
HOWARD BEACH	931
ROSEDALE	922
SPRINGFIELD GARDENS	
SAINT ALBANS	834
KEW GARDENS	771
ROCKAWAY PARK	745
SUNNYSIDE	723
Astoria	716
LITTLE NECK	559
OAKLAND GARDENS	551
CAMBRIA HEIGHTS	477
BELLEROSE	375
GLEN OAKS	306
ARVERNE	220
FLORAL PARK	152
Long Island City	134
Woodside	120
NEW HYDE PARK	98
CENTRAL PARK	97
QUEENS	32
BREEZY POINT	30
East Elmhurst	14
Howard Beach	1
Name: City, dtype: int	64

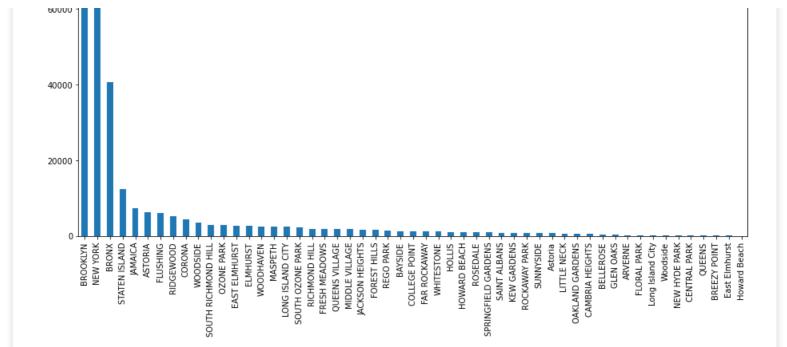
# In [36]:

```
df3.plot(kind='bar',figsize=(15,9),title='Distribution of complaint based on City')
```

# Out[36]:

<AxesSubplot:title={'center':'Distribution of complaint based on City'}>



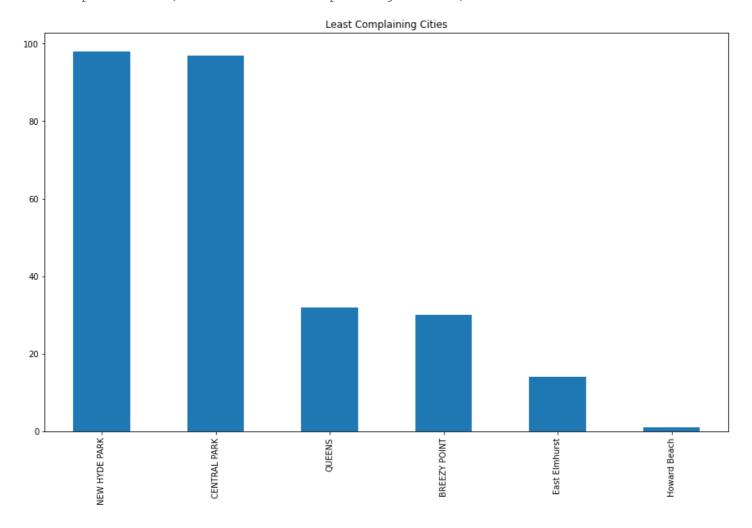


#### In [38]:

```
###Insights on Top 6 complaints
(df['City'].value_counts()).tail(6).plot(kind='bar',figsize=(15,9),title='Least Complain
ing Cities')
```

## Out[38]:

<AxesSubplot:title={'center':'Least Complaining Cities'}>

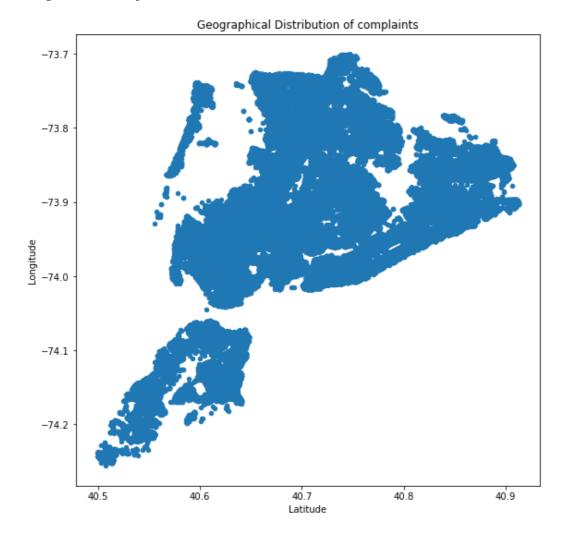


# In [43]:

```
####Geographical Distribution of complaints
df.plot(kind='scatter',x='Latitude',y='Longitude',figsize=(9,9),title='Geographical Dist
ribution of complaints')
```

## Out[43]:

<AxesSubplot:title={'center':'Geographical Distribution of complaints'}, xlabel='Latitude
', ylabel='Longitude'>



# In [44]:

### (4) Order the complaint types based on the average 'Request\_Closing\_Time', grouping them for different locations.

# In [96]:

df\_new=df.groupby(['City','Complaint Type']).Request\_Closing\_Time.mean()
df\_new.head(20)

# Out[96]:

City	Complaint Type	
ARVERNE	Animal Abuse	7753.052632
	Blocked Driveway	9093.485714
	Derelict Vehicle	10685.592593
	Disorderly Youth	12928.500000
	Drinking	859.000000
	Graffiti	5520.000000
	Homeless Encampment	6533.250000
	Illegal Parking	8338.913793
	Noise - Commercial	8234.000000
	Noise - House of Worship	5623.909091
	Noise - Park	4620.000000
	Noise - Street/Sidewalk	7172.620690
	Noise - Vehicle	6695.571429
	Panhandling	3720.000000
	Urinating in Public	2491.000000
	Vending	1740.000000
ASTORIA	Animal Abuse	18000.608000
	Bike/Roller/Skate Chronic	6261.533333
	Blocked Driveway	17338.024064
	Derelict Vehicle	34881.299145
Name: Re	<pre>quest_Closing_Time, dtype:</pre>	float64

```
In [101]:
```

#####Whether the average response time across complaint types is similar or not (overall)

# In [104]:

```
##ANOVA
#h0: mu(Average response time) = mu(Complaint Type)
#hA: mu(Average response time) =! mu(Complaint Type)
from statsmodels.formula.api import ols
import statsmodels.api as sm
df['Complaint_Type'] = df['Complaint Type']
```

#### In [105]:

```
model=ols('Request_Closing_Time ~ Complaint_Type', data=df).fit()
anova_mod=sm.stats.anova_lm(model)
anova_mod
```

### Out[105]:

	df	sum_sq	mean_sq	F	PR(>F)
Complaint_Type	22.0	5.238177e+12	2.380990e+11	514.177089	0.0
Residual	298511.0	1.382309e+14	4.630680e+08	NaN	NaN

### In [106]:

```
##Null hypothesis is rejected as pvalue < 0.05 .
##So, Average response time across complaints are not similar
```

#### In [107]:

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

# In [108]:

```
#h0: mu(Location) = mu(Type of complaint requested)
#hA: mu(Location) != mu(Type of complaint requested)
```

## In [109]:

```
contingency=pd.crosstab(df['Complaint Type'], df['Location Type'])
contingency
```

# Out[109]:

Location Type	Bridge	Club/Bar/Restaurant	Commercial	Highway	House and Store	House of Worship	Park	Park/Playground	Parking Lot	Resid Bu
Complaint Type										
Animal Abuse	0	0	62	0	93	0	0	122	110	
Animal in a Park	0	0	0	0	0	0	1	0	0	
Bike/Roller/Skate Chronic	0	0	0	0	0	0	0	0	0	
Blocked Driveway	0	0	0	0	0	0	0	0	0	
<b>Derelict Vehicle</b>	0	0	0	13	0	0	0	0	0	
Disorderly Youth	0	0	0	0	0	0	0	0	0	
Drinking	0	365	0	0	0	0	0	98	0	
Graffiti	0	0	0	0	0	0	0	0	0	
Homeless Encampment	2	0	0	15	0	0	0	353	0	

Illegal Fireworks Location Type Illegal Parking	0 <b>Bridge</b> 0	0 Club/Bar/Restaurant 0	0 Commercial 0	0 <b>Highway</b> 0	House and Store	Hous <b>e</b> of Worshiß	0 <b>Park</b> 0	8 <b>Park/Playground</b> 0	Parking Lot	Resid Bu
Complain (1998) e Commercial	0	16841	0	0	0	0	0	0	0	
Noise - House of Worship	0	0	0	0	0	927	0	0	0	
Noise - Park	0	0	0	0	0	0	0	4021	0	
Noise - Street/Sidewalk	0	0	0	0	0	0	0	0	0	
Noise - Vehicle	0	0	0	0	0	0	0	0	0	
Panhandling	0	0	0	0	0	0	0	6	0	
Posting Advertisement	0	0	0	0	0	0	0	0	7	
Squeegee	0	0	0	0	0	0	0	0	0	
Traffic	0	0	0	186	0	0	0	0	0	
Urinating in Public	0	21	0	0	0	0	0	38	0	
Vending	0	0	0	0	0	0	0	105	0	
4				13						▶

# In [110]:

contingency\_pcr=pd.crosstab(df['Complaint Type'],df['Location Type'],normalize='index')
contingency\_pcr

Out[110]:

Location Type	Bridge	Club/Bar/Restaurant	Commercial	Highway	House and Store	House of Worship	Park	Park/Playground	Parking Lot
Complaint Type									
Animal Abuse	0.000000	0.000000	0.007985	0.000000	0.011977	0.0	0.0	0.015712	0.014166
Animal in a Park	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	1.0	0.000000	0.000000
Bike/Roller/Skate Chronic	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
Blocked Driveway	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
<b>Derelict Vehicle</b>	0.000000	0.000000	0.000000	0.000739	0.000000	0.0	0.0	0.000000	0.000000
Disorderly Youth	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
Drinking	0.000000	0.286499	0.000000	0.000000	0.000000	0.0	0.0	0.076923	0.000000
Graffiti	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
Homeless Encampment	0.000454	0.000000	0.000000	0.003404	0.000000	0.0	0.0	0.080100	0.000000
Illegal Fireworks	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.047619	0.000000
Illegal Parking	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
Noise - Commercial	0.000000	0.477867	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
Noise - House of Worship	0.000000	0.000000	0.000000	0.000000	0.000000	1.0	0.0	0.000000	0.000000
Noise - Park	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	1.000000	0.000000
Noise - Street/Sidewalk	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
Noise - Vehicle	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
Danhandling	0 000000	0 000000	0 000000	0 000000	0 000000	0.0	0.0	0 010672	0 000000

ганнанчніч	0.000000	0.00000	0.00000	0.000000	0.000000	0.0	0.0	0.013012	0.000000
Location Tipe Advertisement	o. <b>88668</b> 0	Club/Bar/Restauront	Commercial	pistonea	House 0.000000 Store	House 0% Worship	Park	Park/Playground	Parking 0.010818
Сотрынетуре	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.000000	0.000000
Traffic	0.000000	0.000000	0.000000	0.041416	0.000000	0.0	0.0	0.000000	0.000000
Urinating in Public	0.000000	0.035533	0.000000	0.000000	0.000000	0.0	0.0	0.064298	0.000000
Vending	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	0.027683	0.000000

# In [112]:

```
import matplotlib.pyplot as plt
plt.figure(figsize=(8,8))
```

## Out[112]:

<Figure size 576x576 with 0 Axes>
<Figure size 576x576 with 0 Axes>

## In [118]:

```
from scipy.stats import chi2_contingency
c,p,dof,expected=chi2_contingency(contingency)
print('pvalue is:' ,p, 'and dof is', dof)
```

pvalue is: 0.0 and dof is 315

## In [ ]:

#since pvalue is less than 0.05, HO is rejected. So, the type of complaint or service reques ted and location not related.