customer service request analysis python project

June 9, 2021

[1]:
```
#import library
import pandas as pd
import numpy as np
import matplotlib as mpl
from matplotlib import pyplot as plt
%matplotlib inline
plt.style.use(['fivethirtyeight'])
mpl.rcParams['lines.linewidth'] = 3
import warnings
warnings.filterwarnings("ignore")
import scipy.stats as stats
import statsmodels.api as sm
from statsmodels.formula.api import ols
```

[2]:
```
# read data set 311 NYC service request.
df = pd.read_csv('311_Service_Requests_from_2010_to_Present.csv', header=0,
    sep=',', parse_dates=['Created Date', 'Closed Date', 'Resolution Action␣
 ↪Updated Date'],index_col='Unique Key')
```

[3]:
```
#Request_Closing_Time
def prepareData(df):
    df['Resolution_Time'] = (df['Closed Date'] - df['Created Date']).dt.
 ↪total_seconds() ####days/3600
    df_clean=df[df['Resolution_Time'].notnull()]
    df_perfect = df_clean[df_clean['Closed Date'] >= df_clean['Created Date']]
    df_perfect['Day of Week'] = df_perfect['Created Date'].dt.dayofweek
    df_perfect['Day of Month'] = df_perfect['Created Date'].dt.day
    df_perfect['Month'] = df_perfect['Created Date'].dt.month
    df_perfect['Year'] = df_perfect['Created Date'].dt.year
    df_perfect=df_perfect[df_perfect.Borough!='Unspecified']
    return df_perfect
```

[4]:
```
#shape
df_perfect = prepareData(df)
df_perfect.shape
```

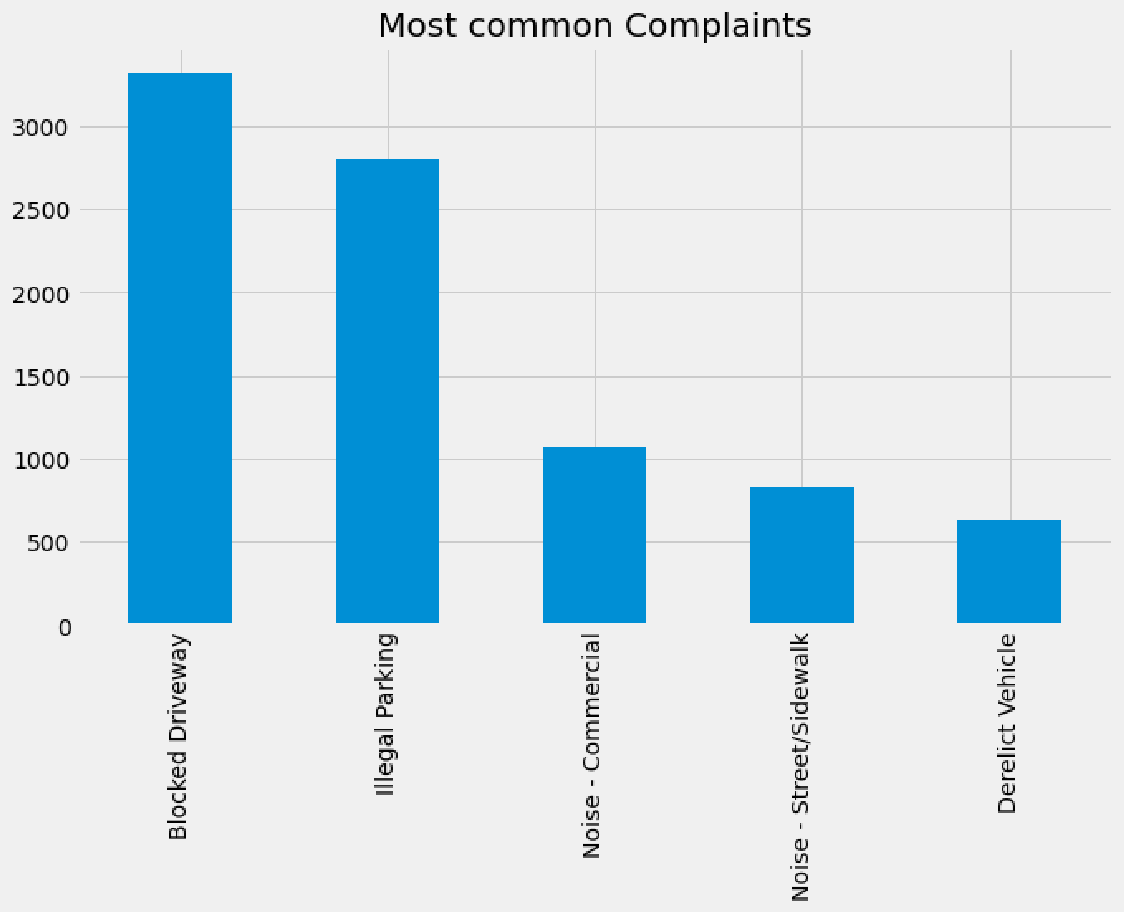
[4]:
```
(9859, 57)
```

[5]:

```
#Major Insights Patterns
#Most frequent Complaints
(df_perfect['Complaint Type'].value_counts()).head().plot(kind='bar',
                    figsize=(10,6), title = 'Most common Complaints')
```

[5]:

```
<AxesSubplot:title={'center':'Most common Complaints'}>
```

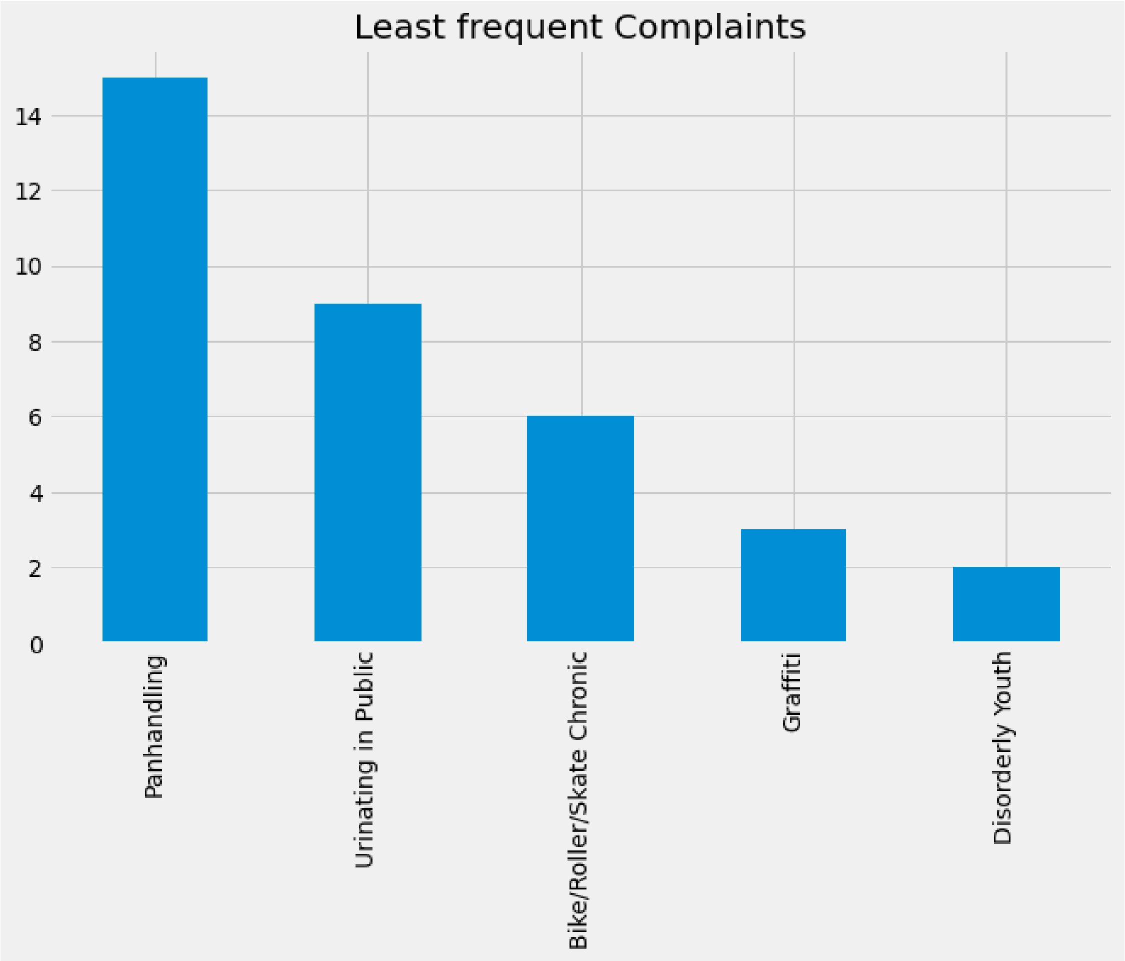


[6]:

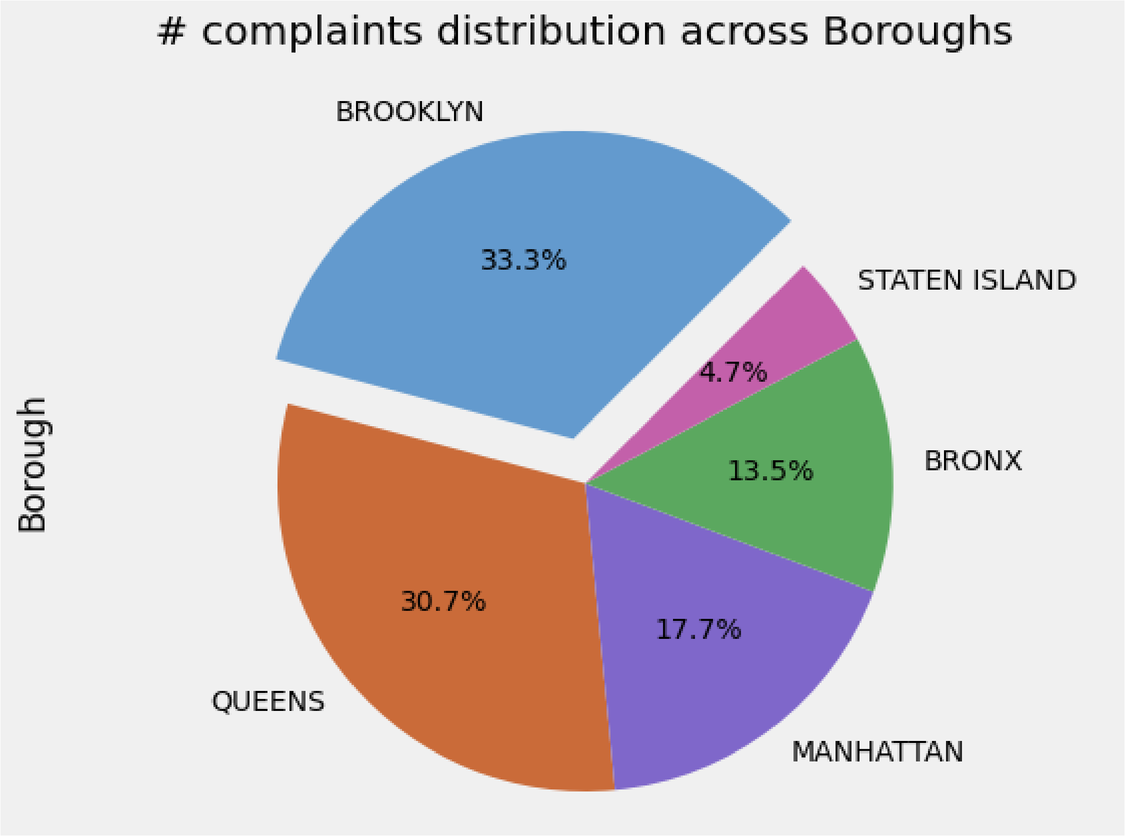
```
#Least frequent Complaints
(df_perfect['Complaint Type'].value_counts()).tail().plot(kind='bar',
                    figsize=(10,6), title = 'Least frequent Complaints')
```

[6]:

```
<AxesSubplot:title={'center':'Least frequent Complaints'}>
```



```
[7]: # complaints distribution across Boroughs
     colors = ['#639ace','#ca6b39','#7f67ca','#5ba85f','#c360aa','#a7993f','#cc566a']
     df_perfect['Borough'].value_counts().plot(kind='pie',autopct='%1.1f%%',
                                 explode = (0.15, 0, 0, 0, 0), startangle=45,␣
      ↪shadow=False, colors = colors,
                                 figsize = (8,6))
     #plt.legend(title='BOROUGH', loc='upper right', bbox_to_anchor=(1.5,1))
     plt.axis('equal')
     plt.title('# complaints distribution across Boroughs\n')
     plt.tight_layout()
     plt.show()
```



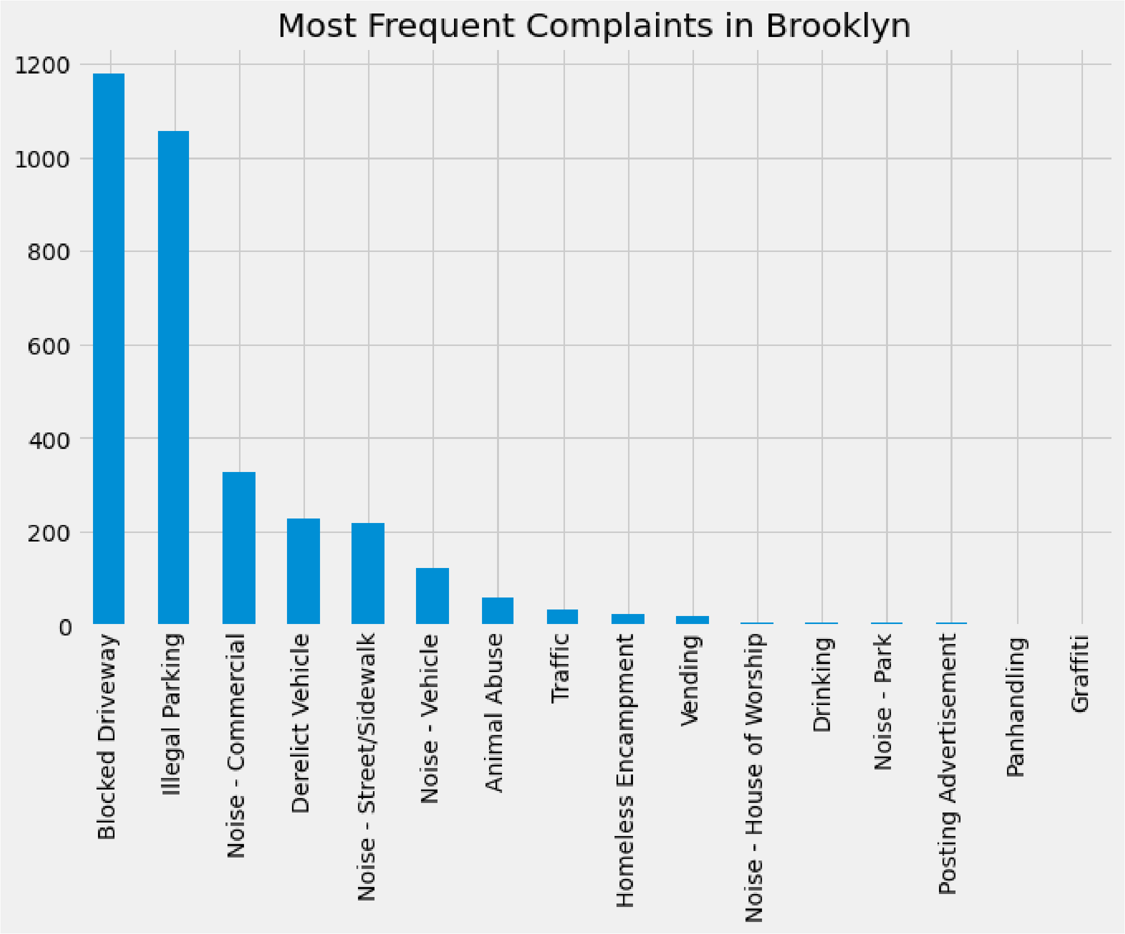
[8]:
```
#Analysis for Brooklyn borough which has highest number of complains
df_Brooklyn = df_perfect[df_perfect['Borough']=='BROOKLYN']
```

[9]:
```
#shape
df_Brooklyn.shape
```

[9]:
```
(3287, 57)
```

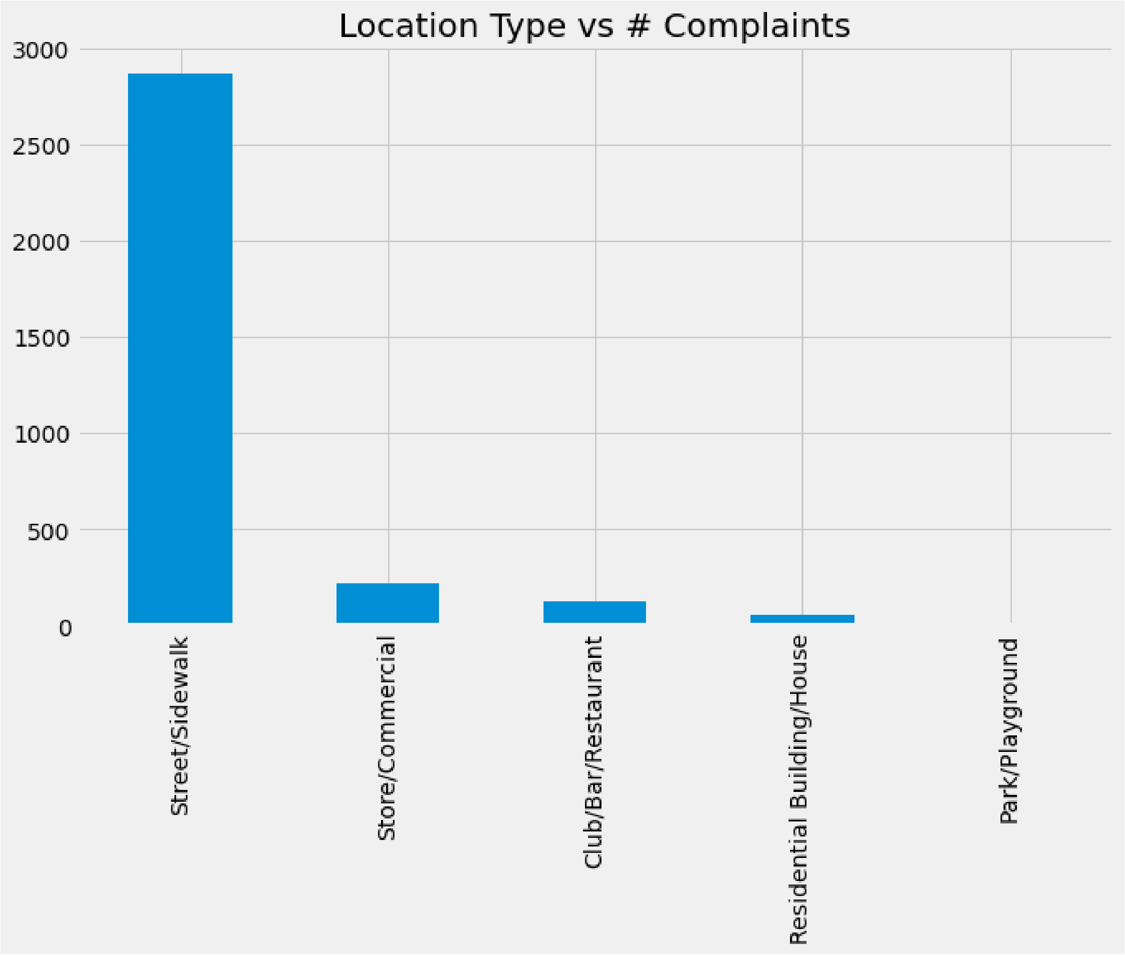
[10]:
```
(df_Brooklyn['Complaint Type'].value_counts()).head(25).plot(kind='bar',
                                                    figsize=(10,6),title =␣
 ↪'Most Frequent Complaints in Brooklyn')
```

[10]:
```
<AxesSubplot:title={'center':'Most Frequent Complaints in Brooklyn'}>
```



```
[11]: #location type vs complaints
      (df_Brooklyn['Location Type'].value_counts()).head().plot(kind='bar',
                                                      figsize=(10,6),title =␣
       ↪'Location Type vs # Complaints')
```

```
[11]: <AxesSubplot:title={'center':'Location Type vs # Complaints'}>
```



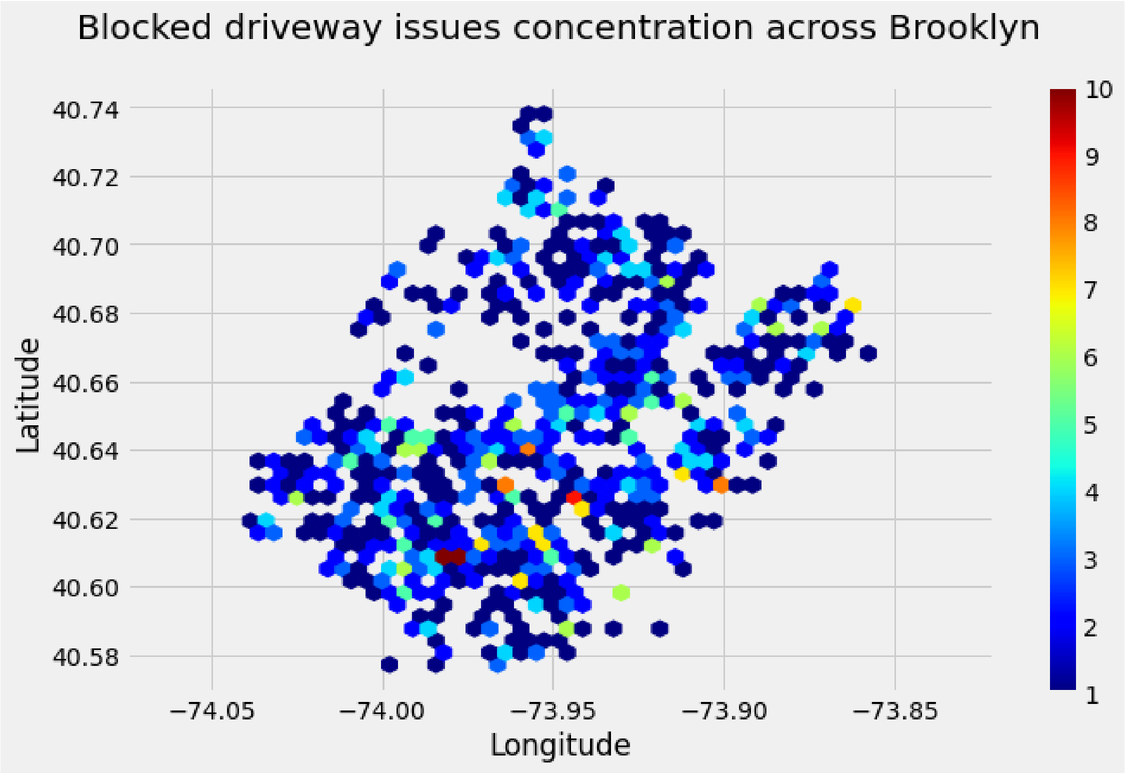
```
[13]: #Anlysis of Most Frequent complaint in Brooklyn
      df_perfect[df_perfect['Complaint Type'] == 'Blocked Driveway']['Descriptor'].
       ↪value_counts()
```

```
[13]: No Access        2519
      Partial Access    798
      Name: Descriptor, dtype: int64
```

```
[14]: df_Brook_blocked = df_Brooklyn[df_Brooklyn['Complaint Type'] == 'Blocked␣
       ↪Driveway']
```

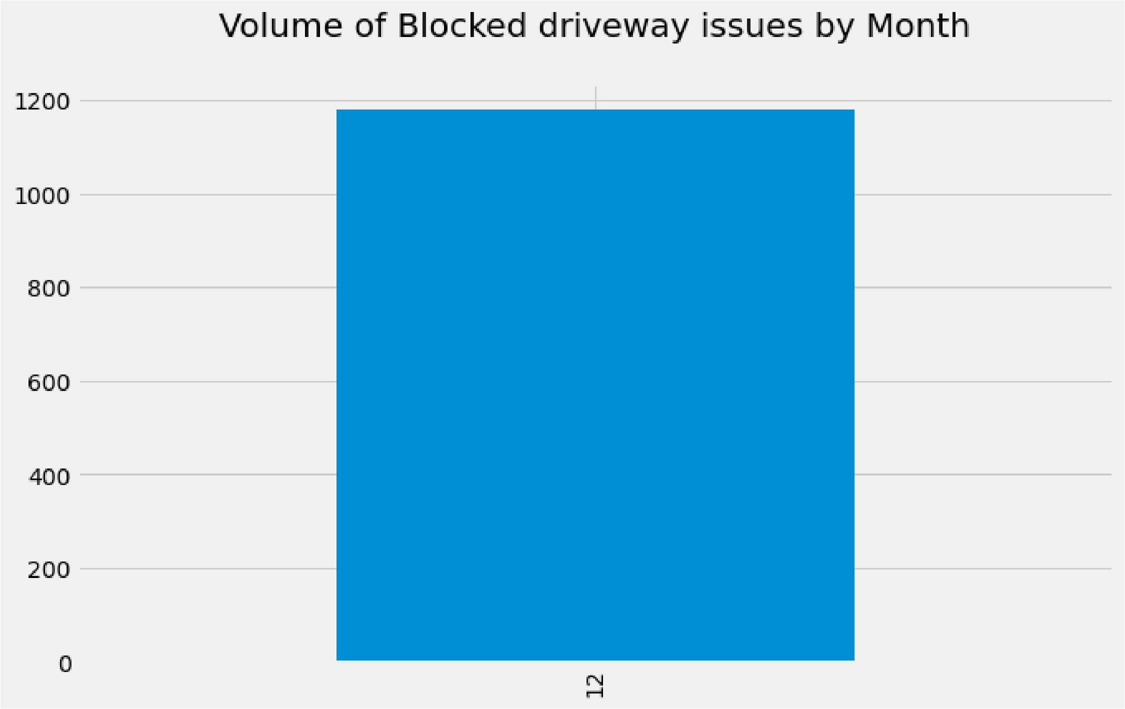
```
[15]: df_Brook_blocked.plot(
          kind='hexbin', x='Longitude', y='Latitude', gridsize=40,title = 'Blocked␣
       ↪driveway issues concentration across Brooklyn\n',
          colormap='jet', mincnt=1, figsize=(10,6)).axis('equal')
```

```
[15]: (-74.04753093769894, -73.84859863230106, 40.5689863275, 40.746125542499996)
```



```
[16]: df_Brook_blocked['Month'].value_counts().plot(kind = 'bar',figsize=(10,6),␣
       ↪title = 'Volume of Blocked driveway issues by Month\n')
```

```
[16]: <AxesSubplot:title={'center':'Volume of Blocked driveway issues by Month\n'}>
```



```
[17]: df_avg_res_time_city = df_perfect.groupby(['City','Complaint Type']).
       ↪Resolution_Time.mean()
      #df_perfect.sort_values('Complaint Type').groupby('City')
      #
      df_avg_res_time_city.head(25)
```

```
[17]: City       Complaint Type
      ARVERNE    Animal Abuse                  5782.500000
                 Illegal Parking              14391.500000
                 Noise - Commercial            5437.000000
      ASTORIA    Animal Abuse                  6719.400000
                 Bike/Roller/Skate Chronic     5101.000000
                 Blocked Driveway             14975.940594
                 Derelict Vehicle             15840.200000
                 Drinking                      6425.000000
                 Homeless Encampment          18789.000000
                 Illegal Parking              13755.479167
                 Noise - Commercial            7852.344828
                 Noise - Street/Sidewalk       9775.666667
                 Noise - Vehicle               8426.777778
      BAYSIDE    Blocked Driveway             10679.000000
                 Derelict Vehicle              7374.600000
                 Illegal Parking               9052.714286
                 Noise - Street/Sidewalk       2031.000000
```

```
           Noise - Vehicle                7054.000000
BELLEROSE  Blocked Driveway               3763.250000
           Derelict Vehicle              55215.000000
           Noise - Commercial             3309.000000
           Noise - Street/Sidewalk       58141.000000
BRONX      Animal Abuse                  45139.710526
           Bike/Roller/Skate Chronic     18530.500000
           Blocked Driveway              27582.763912
Name: Resolution_Time, dtype: float64
```

```
[18]: #Average response time in seconds across complaint types
      df_avg_res_time = df_perfect.groupby('Complaint Type').Resolution_Time.mean().
       ↪sort_values(ascending=True)
      df_avg_res_time.head(21)
```

```
[18]: Complaint Type
      Disorderly Youth              2659.000000
      Posting Advertisement         4817.935484
      Noise - House of Worship      6178.588235
      Urinating in Public           8637.000000
      Bike/Roller/Skate Chronic    10423.000000
      Vending                      10961.470588
      Noise - Commercial           11826.484565
      Noise - Street/Sidewalk      12947.630695
      Panhandling                  13098.733333
      Noise - Vehicle              14086.066838
      Traffic                      14492.788991
      Graffiti                     14967.666667
      Homeless Encampment          15202.952055
      Illegal Parking              15373.488929
      Blocked Driveway             17532.457642
      Animal Abuse                 19210.459350
      Noise - Park                 19496.656250
      Drinking                     23259.475000
      Derelict Vehicle             24489.738437
      Name: Resolution_Time, dtype: float64
```

```
[19]: df_dis_youth = df_perfect[df_perfect['Complaint Type']=='Disorderly Youth']
      df_dis_youth = df_dis_youth.loc[:,['Resolution_Time']]
      df_dis_youth.head()
      #df_dis_youth.columns
      #df_avg_res_time  = df_avg_res_time.to_frame()
      #df_avg_res_time.columns()
      #df_dis_youth.Complaint Type.unique()
```

```
[19]:             Resolution_Time
      Unique Key
```

```
32274507             713.0
32244468            4605.0
```

[20]:

```
df_noise_veh = df_perfect[df_perfect['Complaint Type']=='Noise - Vehicle']
df_noise_veh = df_noise_veh.loc[:,['Resolution_Time']]
df_noise_veh.head()
#df_noise_veh.columns
#df_noise_veh.info()
```

[20]:

```
            Resolution_Time
Unique Key
32307159            22949.0
32308722             7254.0
32308107            11319.0
32308108            10937.0
32306622             2615.0
```

[21]:

```
df_type_res = df_perfect.loc[:, ['Complaint Type','Resolution_Time']]
df_type_res.head()
df_type_res.columns
```

[21]:

```
Index(['Complaint Type', 'Resolution_Time'], dtype='object')
```

[22]:

```
# stats f_oneway functions takes the groups as input and returns F and P-value
fvalue, pvalue = stats.f_oneway(df_dis_youth, df_noise_veh)
pvalue
```

[22]:

```
array([0.45036375])
```

[23]:

```
df_post_ad = df_perfect[df_perfect['Complaint Type']=='Posting Advertisement']
df_post_ad = df_post_ad.loc[:,['Resolution_Time']]
df_post_ad.head()
```

[23]:

```
            Resolution_Time
Unique Key
32306752             7596.0
32307464             7745.0
32308949             7834.0
32307323             8042.0
32306034             8137.0
```

[24]:

```
df_der_veh = df_perfect[df_perfect['Complaint Type']=='Derelict Vehicle']
df_der_veh = df_der_veh.loc[:,['Resolution_Time']]
df_der_veh.head()
```

[24]:

```
            Resolution_Time
Unique Key
```

```
32309424             37763.0
32306497             14221.0
32305124              4913.0
32308002             14879.0
32305798              2712.0
```

[25]:

```
# stats f_oneway functions takes the groups as input and returns F and P-value
fvalue, pvalue = stats.f_oneway(df_post_ad, df_der_veh)
pvalue
```

[25]:

```
array([2.02322069e-05])
```

[26]:

```
# get ANOVA table for complain type and resolution time

# reshape the d dataframe suitable for statsmodels package
df_perfect['Complaint_Type']=df_perfect['Complaint Type']
df_type_res = df_perfect.loc[:, ['Complaint_Type','Resolution_Time']] ␣
 ↪#Complaint Type
# Ordinary Least Squares (OLS) model
model = ols('Resolution_Time ~ Complaint_Type', data=df_type_res).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
anova_table
```

[26]:

```
                      sum_sq      df          F        PR(>F)
Complaint_Type  1.012747e+11    18.0  10.934509  9.822678e-32
Residual        5.063188e+12  9840.0        NaN           NaN
```

[27]:

```
df_city_type = pd.crosstab(df_perfect.City , df_perfect.Complaint_Type)
```

[29]:

```
# chi-squared test with similar proportions
from scipy.stats import chi2_contingency
from scipy.stats import chi2
# contingency table
table = df_city_type
#print(table)
stat, p, dof, expected = chi2_contingency(table)
print('dof=%d' % dof)
print(expected)
# interpret test-statistic
prob = 0.95
critical = chi2.ppf(prob, dof)
print('probability=%.3f, critical=%.3f, stat=%.3f' % (prob, critical, stat))
if abs(stat) >= critical:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
# interpret p-value
```

```python
alpha = 1.0 - prob
print('significance=%.3f, p=%.3f' % (alpha, p))
if p <= alpha:
    print('Dependent (reject H0)')
else:
    print('Independent (fail to reject H0)')
```

```
dof=774
[[1.24759103e-01 3.04290496e-03 1.68221929e+00 3.17983568e-01
  1.01430165e-03 2.02860331e-02 1.52145248e-03 7.40440207e-02
  1.42002231e+00 5.42144234e-01 8.62156405e-03 1.62288265e-02
  4.22963789e-01 1.97281672e-01 7.60726240e-03 3.14433513e-02
  5.52794401e-02 4.56435744e-03 6.89725124e-02]
 [5.33968962e+00 1.30236332e-01 7.19989857e+01 1.36096967e+01
  4.34121108e-02 8.68242215e-01 6.51181661e-02 3.16908409e+00
  6.07769551e+01 2.32037732e+01 3.69002941e-01 6.94593772e-01
  1.81028502e+01 8.44365554e+00 3.25590831e-01 1.34577543e+00
  2.36596004e+00 1.95354498e-01 2.95202353e+00]
 [7.73506441e-01 1.88660108e-02 1.04297596e+01 1.97149812e+00
  6.28867025e-03 1.25773405e-01 9.43300538e-03 4.59072928e-01
  8.80413835e+00 3.36129425e+00 5.34536971e-02 1.00618724e-01
  2.62237549e+00 1.22314636e+00 4.71650269e-02 1.94948778e-01
  3.42732529e-01 2.82990161e-02 4.27629577e-01]
 [2.24566386e-01 5.47722893e-03 3.02799473e+00 5.72370423e-01
  1.82574298e-03 3.65148595e-02 2.73861446e-03 1.33279237e-01
  2.55604017e+00 9.75859621e-01 1.55188153e-02 2.92118876e-02
  7.61334821e-01 3.55107009e-01 1.36930723e-02 5.65980323e-02
  9.95029922e-02 8.21584339e-03 1.24150522e-01]
 [3.31609697e+01 8.08804138e-01 4.47133888e+02 8.45200325e+01
  2.69601379e-01 5.39202759e+00 4.04402069e-01 1.96809007e+01
  3.77441931e+02 1.44101937e+02 2.29161173e+00 4.31362207e+00
  1.12423775e+02 5.24374683e+01 2.02201035e+00 8.35764276e+00
  1.46932752e+01 1.21320621e+00 1.83328938e+01]
 [8.20166345e+01 2.00040572e+00 1.10589096e+03 2.09042398e+02
  6.66801907e-01 1.33360381e+01 1.00020286e+00 4.86765392e+01
  9.33522670e+02 3.56405619e+02 5.66781621e+00 1.06688305e+01
  2.78056395e+02 1.29692971e+02 5.00101430e+00 2.06708591e+01
  3.63407039e+01 3.00060858e+00 4.53425297e+01]
 [1.99614565e-01 4.86864794e-03 2.69155087e+00 5.08773709e-01
  1.62288265e-03 3.24576529e-02 2.43432397e-03 1.18470433e-01
  2.27203570e+00 8.67430774e-01 1.37945025e-02 2.59661223e-02
  6.76742063e-01 3.15650675e-01 1.21716198e-02 5.03093620e-02
  8.84471042e-02 7.30297190e-03 1.10356020e-01]
 [9.23217365e-01 2.25174967e-02 1.24484228e+01 2.35307841e+00
  7.50583223e-03 1.50116645e-01 1.12587484e-02 5.47925753e-01
  1.05081651e+01 4.01186733e+00 6.37995740e-02 1.20093316e-01
  3.12993204e+00 1.45988437e+00 5.62937418e-02 2.32680799e-01
 4.09067857e-01 3.37762451e-02 5.10396592e-01]
[4.54123136e+00 1.10761741e-01 6.12327822e+01 1.15746019e+01
 3.69205802e-02 7.38411604e-01 5.53808703e-02 2.69520235e+00
 5.16888123e+01 1.97340501e+01 3.13824932e-01 5.90729283e-01
 1.53958819e+01 7.18105285e+00 2.76904351e-01 1.14453799e+00
 2.01217162e+00 1.66142611e-01 2.51059945e+00]
[2.44527843e+00 5.96409372e-02 3.29714981e+01 6.23247794e+00
 1.98803124e-02 3.97606248e-01 2.98204686e-02 1.45126281e+00
 2.78324374e+01 1.06260270e+01 1.68982655e-01 3.18084998e-01
 8.29009027e+00 3.86672076e+00 1.49102343e-01 6.16289685e-01
 1.08347703e+00 8.94614058e-02 1.35186124e+00]
[3.31859215e+00 8.09412719e-02 4.47470332e+01 8.45836292e+00
 2.69804240e-02 5.39608480e-01 4.04706360e-02 1.96957095e+00
 3.77725936e+01 1.44210366e+01 2.29333604e-01 4.31686784e-01
 1.12508368e+01 5.24769246e+00 2.02353180e-01 8.36393143e-01
 1.47043311e+00 1.21411908e-01 1.83466883e+00]
[7.73506441e-01 1.88660108e-02 1.04297596e+01 1.97149812e+00
 6.28867025e-03 1.25773405e-01 9.43300538e-03 4.59072928e-01
 8.80413835e+00 3.36129425e+00 5.34536971e-02 1.00618724e-01
 2.62237549e+00 1.22314636e+00 4.71650269e-02 1.94948778e-01
 3.42732529e-01 2.82990161e-02 4.27629577e-01]
[4.99036413e-02 1.21716198e-03 6.72887717e-01 1.27193427e-01
 4.05720661e-04 8.11441323e-03 6.08580992e-04 2.96176083e-02
 5.68008926e-01 2.16857693e-01 3.44862562e-03 6.49153058e-03
 1.69185516e-01 7.89126686e-02 3.04290496e-03 1.25773405e-02
 2.21117760e-02 1.82574298e-03 2.75890050e-02]
[6.56232884e+00 1.60056801e-01 8.84847348e+01 1.67259357e+01
 5.33522670e-02 1.06704534e+00 8.00284004e-02 3.89471549e+00
 7.46931737e+01 2.85167867e+01 4.53494269e-01 8.53636271e-01
 2.22478953e+01 1.03770159e+01 4.00142002e-01 1.65392028e+00
 2.90769855e+00 2.40085201e-01 3.62795415e+00]
[1.74662745e+00 4.26006694e-02 2.35510701e+01 4.45176996e+00
 1.42002231e-02 2.84004463e-01 2.13003347e-02 1.03661629e+00
 1.98803124e+01 7.59001927e+00 1.20701897e-01 2.27203570e-01
 5.92149305e+00 2.76194340e+00 1.06501674e-01 4.40206918e-01
 7.73912161e-01 6.39010042e-02 9.65615174e-01]
[3.01917030e+00 7.36383000e-02 4.07097069e+01 7.69520235e+00
 2.45461000e-02 4.90922000e-01 3.68191500e-02 1.79186530e+00
 3.43645400e+01 1.31198905e+01 2.08641850e-01 3.92737600e-01
 1.02357237e+01 4.77421645e+00 1.84095750e-01 7.60929100e-01
 1.33776245e+00 1.10457450e-01 1.66913480e+00]
[2.24566386e-01 5.47722893e-03 3.02799473e+00 5.72370423e-01
 1.82574298e-03 3.65148595e-02 2.73861446e-03 1.33279237e-01
 2.55604017e+00 9.75859621e-01 1.55188153e-02 2.92118876e-02
 7.61334821e-01 3.55107009e-01 1.36930723e-02 5.65980323e-02
 9.95029922e-02 8.21584339e-03 1.24150522e-01]
[9.98072827e-01 2.43432397e-02 1.34577543e+01 2.54386855e+00
 8.11441323e-03 1.62288265e-01 1.21716198e-02 5.92352166e-01
 1.13601785e+01 4.33715387e+00 6.89725124e-02 1.29830612e-01
 3.38371032e+00 1.57825337e+00 6.08580992e-02 2.51546810e-01
 4.42235521e-01 3.65148595e-02 5.51780099e-01]
[9.73121006e-01 2.37346587e-02 1.31213105e+01 2.48027183e+00
 7.91155290e-03 1.58231058e-01 1.18673293e-02 5.77543361e-01
 1.10761741e+01 4.22872502e+00 6.72481996e-02 1.26584846e-01
 3.29911756e+00 1.53879704e+00 5.93366467e-02 2.45258140e-01
 4.31179633e-01 3.56019880e-02 5.37985597e-01]
[1.52206106e+00 3.71234405e-02 2.05230754e+01 3.87939953e+00
 1.23744802e-02 2.47489603e-01 1.85617203e-02 9.03337052e-01
 1.73242722e+01 6.61415965e+00 1.05183081e-01 1.97991683e-01
 5.16015823e+00 2.40683639e+00 9.28086013e-02 3.83608885e-01
 6.74409169e-01 5.56851608e-02 8.41464652e-01]
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