Project_Customer Service Requests Analysis

November 7, 2022

```
[1]: import warnings
     warnings.filterwarnings('ignore')
[2]: import pandas as pd
     import numpy as np
     data = pd.read_csv('311_Service_Requests_from_2010.csv')
[4]:
     data.head()
[4]:
        Unique Key
                              Created Date
                                                        Closed Date Agency
          32310363
                    12/31/2015 11:59:45 PM
                                             01/01/2016 12:55:15 AM
                                                                       NYPD
     1
          32309934
                    12/31/2015 11:59:44 PM
                                             01/01/2016 01:26:57 AM
                                                                       NYPD
     2
          32309159 12/31/2015 11:59:29 PM
                                             01/01/2016 04:51:03 AM
                                                                       NYPD
     3
          32305098 12/31/2015 11:57:46 PM
                                             01/01/2016 07:43:13 AM
                                                                       NYPD
          32306529 12/31/2015 11:56:58 PM
                                             01/01/2016 03:24:42 AM
                                                                       NYPD
                            Agency Name
                                                   Complaint Type
       New York City Police Department
                                         Noise - Street/Sidewalk
       New York City Police Department
                                                 Blocked Driveway
       New York City Police Department
                                                 Blocked Driveway
       New York City Police Department
                                                  Illegal Parking
       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
                    Blocked Sidewalk
                                      Street/Sidewalk
                                                             11373.0
                               ... Bridge Highway Name Bridge Highway Direction
             Incident Address
     0
          71 VERMILYEA AVENUE
                                                  NaN
                                                                            NaN
     1
              27-07 23 AVENUE
                                                  NaN
                                                                            NaN
        2897 VALENTINE AVENUE
                                                  NaN
                                                                            NaN
     3
          2940 BAISLEY AVENUE
                                                  NaN
                                                                            NaN
                87-14 57 ROAD
                                                  NaN
                                                                            NaN
```

```
Road Ramp Bridge Highway Segment Garage Lot Name Ferry Direction \
0
        NaN
                                 NaN
                                                  NaN
                                                                   NaN
                                                  NaN
        NaN
                                 NaN
                                                                   NaN
1
2
        NaN
                                 NaN
                                                  NaN
                                                                   NaN
3
        NaN
                                 NaN
                                                  NaN
                                                                   NaN
4
        NaN
                                 NaN
                                                  NaN
                                                                   NaN
  Ferry Terminal Name
                         Latitude Longitude
0
                        40.865682 -73.923501
1
                   NaN
                        40.775945 -73.915094
2
                   {\tt NaN}
                        40.870325 -73.888525
3
                   {\tt NaN}
                        40.835994 -73.828379
4
                        40.733060 -73.874170
                   {\tt NaN}
                                     Location
0
    (40.86568153633767, -73.92350095571744)
   (40.775945312321085, -73.91509393898605)
1
  (40.870324522111424, -73.88852464418646)
    (40.83599404683083, -73.82837939584206)
3
  (40.733059618956815, -73.87416975810375)
[5 rows x 53 columns]
```

[5]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 364558 entries, 0 to 364557

Data columns (total 53 columns):

#	Column	Non-Null Count	Dtype
0	Unique Key	364558 non-null	int64
1	Created Date	364558 non-null	object
2	Closed Date	362177 non-null	object
3	Agency	364558 non-null	object
4	Agency Name	364558 non-null	object
5	Complaint Type	364558 non-null	object
6	Descriptor	358057 non-null	object
7	Location Type	364425 non-null	object
8	Incident Zip	361560 non-null	float64
9	Incident Address	312859 non-null	object
10	Street Name	312859 non-null	object
11	Cross Street 1	307370 non-null	object
12	Cross Street 2	306753 non-null	object
13	Intersection Street 1	51120 non-null	object
14	Intersection Street 2	50512 non-null	object
15	Address Type	361306 non-null	object

16	City	361561 non-null	object
17	Landmark	375 non-null	object
18	Facility Type	362169 non-null	object
19	Status	364558 non-null	object
20	Due Date	364555 non-null	object
21	Resolution Description	364558 non-null	object
22	Resolution Action Updated Date	362156 non-null	object
23	Community Board	364558 non-null	object
24	Borough	364558 non-null	object
25	X Coordinate (State Plane)	360528 non-null	float64
26	Y Coordinate (State Plane)	360528 non-null	float64
27	Park Facility Name	364558 non-null	object
28	Park Borough	364558 non-null	object
29	School Name	364558 non-null	object
30	School Number	364558 non-null	object
31	School Region	364557 non-null	object
32	School Code	364557 non-null	object
33	School Phone Number	364558 non-null	object
34	School Address	364558 non-null	object
35	School City	364558 non-null	object
36	School State	364558 non-null	object
37	School Zip	364557 non-null	object
38	School Not Found	364558 non-null	object
39	School or Citywide Complaint	0 non-null	float64
40	Vehicle Type	0 non-null	float64
41	Taxi Company Borough	0 non-null	float64
42	Taxi Pick Up Location	0 non-null	float64
43	Bridge Highway Name	297 non-null	object
44	Bridge Highway Direction	297 non-null	object
45	Road Ramp	262 non-null	object
46	Bridge Highway Segment	262 non-null	object
47	Garage Lot Name	0 non-null	float64
48	Ferry Direction	1 non-null	object
49	Ferry Terminal Name	2 non-null	object
50	Latitude	360528 non-null	float64
51	Longitude	360528 non-null	float64
52	Location	360528 non-null	object

dtypes: float64(10), int64(1), object(42)

memory usage: 147.4+ MB

1 1. Understand the dataset:

- 1. Identify the shape of the dataset
- 2. Identify variables with null values

[6]: # Identify the shape of the dataset data.shape

[6]: (364558, 53)

[7]: data.shape[0]

[7]: 364558

[8]: # Identify variables with null values data.isna().sum()

[8]:	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

dtype: int64

[9]: data.isna().sum()/data.shape[0]

[9]:	Unique Key	0.000000
	Created Date	0.00000
	Closed Date	0.006531
	Agency	0.000000
	Agency Name	0.000000
	Complaint Type	0.000000
	Descriptor	0.017833
	Location Type	0.000365
	Incident Zip	0.008224
	Incident Address	0.141813
	Street Name	0.141813
	Cross Street 1	0.156869
	Cross Street 2	0.158562
	Intersection Street 1	0.859775
	Intersection Street 2	0.861443
	Address Type	0.008920
	City	0.008221
	Landmark	0.998971
	Facility Type	0.006553
	Status	0.000000
	Due Date	0.000008
	Resolution Description	0.000000
	Resolution Action Updated Date	0.006589
	Community Board	0.000000
	Borough	0.000000

X Coordinate (State Plane)	0.011054
Y Coordinate (State Plane)	0.011054
Park Facility Name	0.000000
Park Borough	0.000000
School Name	0.000000
School Number	0.000000
School Region	0.000003
School Code	0.000003
School Phone Number	0.000000
School Address	0.000000
School City	0.000000
School State	0.000000
School Zip	0.000003
School Not Found	0.000000
School or Citywide Complaint	1.000000
Vehicle Type	1.000000
Taxi Company Borough	1.000000
Taxi Pick Up Location	1.000000
Bridge Highway Name	0.999185
Bridge Highway Direction	0.999185
Road Ramp	0.999281
Bridge Highway Segment	0.999281
Garage Lot Name	1.000000
Ferry Direction	0.999997
Ferry Terminal Name	0.999995
Latitude	0.011054
Longitude	0.011054
Location	0.011054
d+	

dtype: float64

2 2. Perform basic data exploratory analysis:

- 1. Utilize missing value treatment
- 2. Analyze the date column and remove the entries if it has an incorrect timeline
- 3. Draw a frequency plot for city-wise complaints
- 4. Draw scatter and hexbin plots for complaint concentration across Brooklyn

```
[10]: # data=data.drop(columns=['School Name', 'School Number', 'School Region', 'School \_ \_\circ Code', 'School Phone Number',

# 'School Address', 'School City', 'School State', 'School \_\circ \_\circ Zip', 'School Not Found',

# 'School or Citywide Complaint', 'Unique\_\circ \_Key', 'Agency', 'Vehicle Type', 'Taxi Company Borough',
```

```
# 'Taxi Pick Up Location', 'Garage Lot Name', 'Ferry
→Direction', 'Ferry Terminal Name'], axis=1)
# data.head()
```

[11]: # 1. Utilize missing value treatment

data_imputed = data.fillna(0)
round((data_imputed.isna().sum() / data_imputed.shape[0])*100)

Г117:	Unique Key	0.0
	Created Date	0.0
	Closed Date	0.0
	Agency	0.0
	Agency Name	0.0
	Complaint Type	0.0
	Descriptor	0.0
	Location Type	0.0
	Incident Zip	0.0
	Incident Address	0.0
	Street Name	0.0
	Cross Street 1	0.0
	Cross Street 2	0.0
	Intersection Street 1	0.0
	Intersection Street 2	0.0
	Address Type	0.0
	City	0.0
	Landmark	0.0
	Facility Type	0.0
	Status	0.0
	Due Date	0.0
	Resolution Description	0.0
	Resolution Action Updated Date	0.0
	Community Board	0.0
	Borough	0.0
	X Coordinate (State Plane)	0.0
	Y Coordinate (State Plane)	0.0
	Park Facility Name	0.0
	Park Borough	0.0
	School Name	0.0
	School Number	0.0
	School Region	0.0
	School Code	0.0
	School Phone Number	0.0
	School Address	0.0
	School City	0.0
	School State	0.0
	School Zip	0.0

```
School or Citywide Complaint
                                        0.0
      Vehicle Type
                                        0.0
      Taxi Company Borough
                                        0.0
      Taxi Pick Up Location
                                        0.0
      Bridge Highway Name
                                        0.0
     Bridge Highway Direction
                                        0.0
      Road Ramp
                                        0.0
      Bridge Highway Segment
                                        0.0
      Garage Lot Name
                                        0.0
     Ferry Direction
                                        0.0
     Ferry Terminal Name
                                        0.0
     Latitude
                                        0.0
      Longitude
                                        0.0
                                        0.0
      Location
      dtype: float64
[12]: \# 2. Analyze the date column and remove the entries if it has an incorrect
      \rightarrow timeline
      data['Created Date'] = pd.to_datetime(data['Created Date'])
      data['Closed Date'] = pd.to datetime(data['Closed Date'])
      data['Due Date'] = pd.to_datetime(data['Due Date'])
      data_date = data[['Created Date','Closed Date']]
[13]: data_date.info()
     <class 'pandas.core.frame.DataFrame'>
     RangeIndex: 364558 entries, 0 to 364557
     Data columns (total 2 columns):
      #
          Column
                        Non-Null Count
                                          Dtype
                        _____
          Created Date 364558 non-null datetime64[ns]
          Closed Date
                        362177 non-null datetime64[ns]
     dtypes: datetime64[ns](2)
     memory usage: 5.6 MB
[14]: data_date.head()
[14]:
               Created Date
                                    Closed Date
      0 2015-12-31 23:59:45 2016-01-01 00:55:15
      1 2015-12-31 23:59:44 2016-01-01 01:26:57
      2 2015-12-31 23:59:29 2016-01-01 04:51:03
      3 2015-12-31 23:57:46 2016-01-01 07:43:13
      4 2015-12-31 23:56:58 2016-01-01 03:24:42
```

0.0

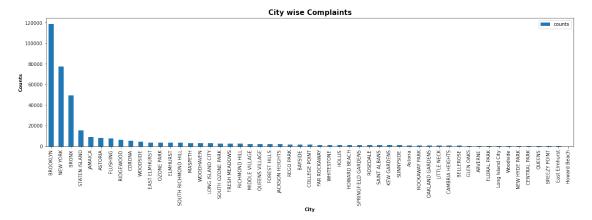
School Not Found

[15]:		City	counts	Percentage	
	0	•	118862	32.87	
	1	NEW YORK	77312	21.38	
	2	BRONX	49171	13.60	
	3	STATEN ISLAND	15340	4.24	
	4	JAMAICA	8932	2.47	
	5	ASTORIA	7991	2.21	
	6	FLUSHING	7487	2.07	
	7	RIDGEWOOD	6392	1.77	
	8	CORONA	5383	1.49	
	9	WOODSIDE	4357	1.21	
	10	EAST ELMHURST	3558	0.98	
	11	OZONE PARK	3446	0.95	
	12	ELMHURST	3438	0.95	
	13	SOUTH RICHMOND HILL	3431	0.95	
	14	MASPETH	3118	0.86	
	15	WOODHAVEN	3103	0.86	
	16	LONG ISLAND CITY	3028	0.84	
	17	SOUTH OZONE PARK	2668	0.74	
	18	FRESH MEADOWS	2453	0.68	
	19	RICHMOND HILL	2335	0.65	
	20	MIDDLE VILLAGE	2291	0.63	
	21	QUEENS VILLAGE	2251	0.62	
	22	FOREST HILLS	2122	0.59	
	23	JACKSON HEIGHTS	2106	0.58	
	24	REGO PARK	1807	0.50	
	25	BAYSIDE	1550	0.43	
	26	COLLEGE POINT	1544	0.43	
	27	FAR ROCKAWAY	1397	0.39	
	28	WHITESTONE	1369	0.38	
	29	HOLLIS	1231	0.34	
	30	HOWARD BEACH	1144	0.32	
	31	SPRINGFIELD GARDENS	1094	0.30	
	32	ROSEDALE	1091	0.30	
	33	SAINT ALBANS	1047	0.29	
	34	KEW GARDENS	1008	0.28	
	35 36	SUNNYSIDE	944	0.26 0.25	
		Astoria ROCKAWAY PARK	906 931	0.25	
	37	RUCKAWAI PARK	831	0.23	

```
OAKLAND GARDENS
                                         0.20
38
                              717
39
            LITTLE NECK
                              712
                                         0.20
40
                                         0.17
        CAMBRIA HEIGHTS
                              617
41
               BELLEROSE
                              487
                                         0.13
42
               GLEN OAKS
                              361
                                         0.10
43
                 ARVERNE
                              259
                                         0.07
                                         0.05
44
            FLORAL PARK
                              196
45
       Long Island City
                                         0.05
                              170
                Woodside
                                         0.05
46
                              166
          NEW HYDE PARK
47
                              129
                                         0.04
           CENTRAL PARK
                                         0.03
48
                              110
49
                  QUEENS
                               37
                                         0.01
50
           BREEZY POINT
                               31
                                         0.01
          East Elmhurst
                               30
                                         0.01
51
52
           Howard Beach
                                1
                                         0.00
```

[16]: import matplotlib.pyplot as plt

```
[17]: data_city.plot(x='City',y='counts',kind='bar',figsize=(20,5))
    plt.title('City wise Complaints',fontsize=15,weight='bold')
    plt.xlabel('City',weight='bold')
    plt.ylabel('Counts',weight='bold')
    plt.show()
```



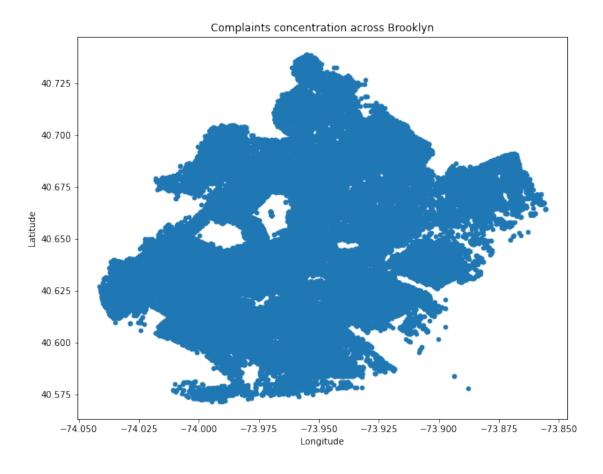
[18]: # 4. Draw scatter and hexbin plots for complaint concentration across Brooklyn data['Borough'].value_counts()

[18]: BROOKLYN 118864
QUEENS 100766
MANHATTAN 77462
BRONX 49169
STATEN ISLAND 15339

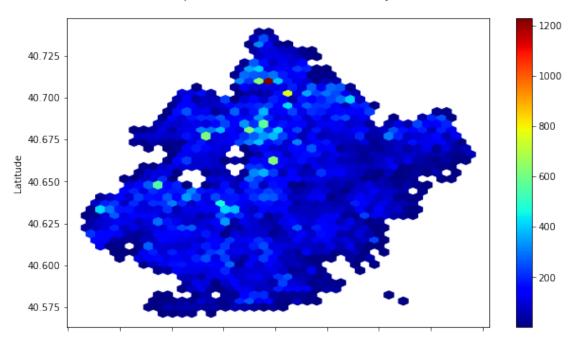
Unspecified 2958
Name: Borough, dtype: int64

```
[19]: data_brooklyn = data[data['Borough'] == 'BROOKLYN']
data_brooklyn.shape
```

[19]: (118864, 53)





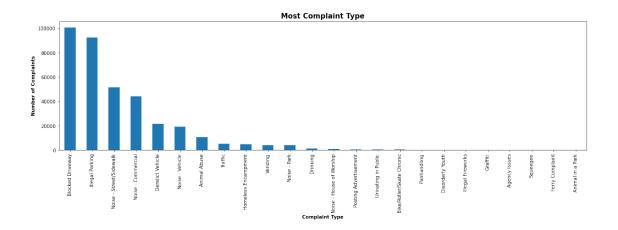


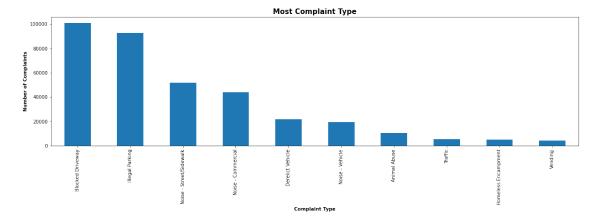
3 3. Find major types of complaints:

- 1. Plot a bar graph of count vs. complaint types
- 2. Find the top 10 types of complaints
- 3. Display the types of complaints in each city in a separate dataset

```
[22]: # 1. Plot a bar graph of count vs. complaint types
data_complaint = data['Complaint Type'].value_counts().

→plot(kind='bar',figsize=(20,5))
plt.xlabel('Complaint Type',weight='bold',fontsize=10)
plt.ylabel('Number of Complaints',weight='bold',fontsize=10)
plt.title('Most Complaint Type',weight='bold',fontsize=15)
plt.show()
```





```
[24]: # 3. Display the types of complaints in each city in a separate dataset city_complaint = data.groupby(['Complaint Type','City'],as_index=False)['City'].

→size()
city_complaint.rename(columns={'size':'Counts'})
```

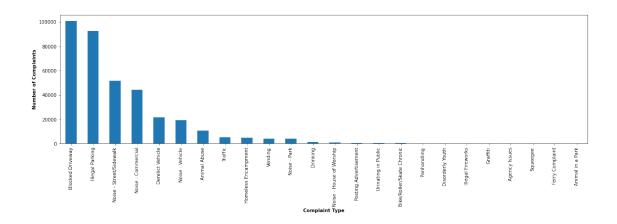
[24]:		Complaint Type	City	Counts
	0	Animal Abuse	ARVERNE	46
	1	Animal Abuse	ASTORIA	170
	2	Animal Abuse	BAYSIDE	53

```
Animal Abuse
3
                         BELLEROSE
                                         15
4
      Animal Abuse
                                          2
                      BREEZY POINT
772
                                         25
           Vending
                    STATEN ISLAND
773
           Vending
                         SUNNYSIDE
                                         15
774
           Vending
                        WHITESTONE
                                          1
775
           Vending
                         WOODHAVEN
                                          6
776
           Vending
                          WOODSIDE
                                         15
```

[777 rows x 3 columns]

4 4. Visualize the major types of complaints in each city

```
[25]: complaint_city = data.groupby(['City', 'Complaint_
       →Type'],as_index=False)['Complaint Type'].size()
      complaint_city.rename(columns={'size':'Counts'})
[25]:
               City
                              Complaint Type
                                              Counts
                                Animal Abuse
      0
            ARVERNE
                                                   46
                            Blocked Driveway
      1
            ARVERNE
                                                   50
      2
            ARVERNE
                            Derelict Vehicle
                                                   32
                            Disorderly Youth
      3
            ARVERNE
                                                    2
      4
            ARVERNE
                                    Drinking
                                                    1
      772 Woodside
                            Blocked Driveway
                                                   27
      773 Woodside
                            Derelict Vehicle
                                                    8
      774 Woodside
                             Illegal Parking
                                                  124
                          Noise - Commercial
      775 Woodside
                                                    2
      776 Woodside Noise - Street/Sidewalk
                                                    5
      [777 rows x 3 columns]
[26]: data['Complaint Type'].value_counts().plot(kind='bar',figsize=(20,5))
      plt.xlabel('Complaint Type', weight='bold', fontsize=10)
      plt.ylabel('Number of Complaints', weight='bold', fontsize=10)
      plt.show()
```



5 5. Check if the average response time across various types of complaints

```
[27]: data_date['Request_Response_Time'] = data['Closed Date'] - data['Created Date']
      data_date['Request_Response_Time'].head()
[27]: 0
          0 days 00:55:30
          0 days 01:27:13
      1
          0 days 04:51:34
      2
      3
          0 days 07:45:27
          0 days 03:27:44
      Name: Request_Response_Time, dtype: timedelta64[ns]
[28]: data_date['Request_Response_Time'].describe()
[28]: count
                                  362177
     mean
               0 days 04:11:53.299632500
               0 days 05:51:42.547519569
      std
                         0 days 00:01:01
      min
      25%
                         0 days 01:15:33
      50%
                         0 days 02:40:16
      75%
                         0 days 05:14:38
                        24 days 16:52:22
      max
      Name: Request_Response_Time, dtype: object
```

• 04 hrs 11 min 53 sec average response time across various types of complaints

6 6. Identify significant variables by performing a statistical analysis using p-values and chi-square values

```
[29]: from scipy import stats
[30]: # help(stats.chi2_contingency)
[31]: data_cross = pd.crosstab(data['Complaint Type'],data['City'])
[32]: coff,pval,dof,expec=stats.chi2_contingency(data_cross)
      print("chisquare",coff)
      print("Pvalue",pval)
      print("DOF",dof)
      print("Expected", expec)
     chisquare 141373.60935271924
     Pvalue 0.0
     DOF 1092
     Expected [[7.54232619e+00 2.32705516e+02 2.63835812e+01 ... 9.03623095e+01
       1.26879982e+02 4.83407779e+00]
      [7.16338322e-04 2.21013881e-02 2.50580123e-03 ... 8.58223094e-03
       1.20505254e-02 4.59120314e-04]
      [3.38828026e-01 1.04539566e+01 1.18524398e+00 ... 4.05939523e+00
       5.69989850e+00 2.17163909e-01]
      [3.72137758e+00 1.14816711e+02 1.30176374e+01 ... 4.45846897e+01
       6.26024792e+01 2.38513003e+00]
      [4.59172864e-01 1.41669898e+01 1.60621859e+00 ... 5.50121003e+00
       7.72438676e+00 2.94296122e-01]
      [2.99787588e+00 9.24943094e+01 1.04867782e+01 ... 3.59166365e+01
       5.04314486e+01 1.92141852e+00]]
[33]: | if pval<0.05:
          print("Alter Hypo---->relation exist")
      else:
          print("Null Hypo---->No relation")
     Alter Hypo---->relation exist
 []:
```