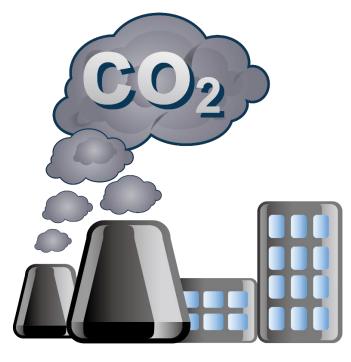
International Information Technology University

Faculty of Computer Technology and Cybersecurity



Air Pollution

Done by: Aibek Shynazbek, Nurkanat Demesin

Group: IT2-2107

Check by: Meruyert T. Aristombayeva

- I. Project topic: Air Pollution
- II. Project description: Air pollution is one of the most important environmental threats to urban populations, and although all people are exposed to it, pollutant emissions, exposure levels and population vulnerabilities vary from area to area. Exposure to common air pollutants has been linked to respiratory and cardiovascular disease, cancer, and premature death. These indicators provide a measure of air quality and public health in New York City over time and across geographic areas of the city.
- III. Dataset description: Dataset contains information on New York City air quality surveillance data in a 16122 row. Link: https://catalog.data.gov/dataset/air-quality.

IV. Research questions:

Descriptive	Diagnostic	Predictive
1. Which area has the most	1. How does geographic	1. Predicting future
pollution?	type affect the pollution	pollution based on
2. Which indicator pollutes	indicator?	time period.
the air the most?		

V. Dataset screenshot:

	Α	В	С	D	E	F	G	Н		J	K	L
1	Unique ID	Indicator I	Name	Measure	Measure I	Geo Type	l Geo Join II	Geo Place	Time Peric	Start Date	Data Value	Message
2	216498	386	Ozone (O3	Mean	ppb	CD	313	Coney Isla	Summer 2	6/1/2013	34.64	
3	216499	386	Ozone (O3	Mean	ppb	CD	313	Coney Isla	Summer 20	6/1/2014	33.22	
4	219969	386	Ozone (O3	Mean	ppb	Borough	1	Bronx	Summer 20	6/1/2013	31.25	
5	219970	386	Ozone (O3	Mean	ppb	Borough	1	Bronx	Summer 20	6/1/2014	31.15	
6	164876	383	Sulfur Diox	Mean	ppb	CD	211	Morris Par	Winter 200	########	5.89	
7	164877	383	Sulfur Diox	Mean	ppb	CD	212	Williamsbr	Winter 200	########	5.75	
8	219971	386	Ozone (O3	Mean	ppb	Borough	2	Brooklyn	Summer 20	6/1/2009	26.27	
9	219972	386	Ozone (O3	Mean	ppb	Borough	2	Brooklyn	Summer 20	6/1/2010	33.83	
10	164878	383	Sulfur Diox	Mean	ppb	CD	301	Greenpoin	Winter 200	########	4.33	
11	164879	383	Sulfur Diox	Mean	ppb	CD	302	Fort Green	Winter 200	########	4.41	
12	164880	383	Sulfur Diox	Mean	ppb	CD	303	Bedford St	Winter 200	########	4.73	
13	164881	383	Sulfur Diox	Mean	ppb	CD	304	Bushwick (Winter 200	########	4.71	
14	164882	383	Sulfur Diox	Mean	ppb	CD	305	East New '	Winter 200	########	3.78	
15	164883	383	Sulfur Diox	Mean	ppb	CD	306	Park Slope	Winter 200	#######	3.94	
16	164884	383	Sulfur Diox	Mean	ppb	CD	307	Sunset Par	Winter 200	########	3.78	
17	164885	383	Sulfur Diox	Mean	ppb	CD	308	Crown Hei	Winter 200	#######	4.79	
18	219973	386	Ozone (O3	Mean	ppb	Borough	2	Brooklyn	Summer 20	6/1/2011	33.19	
19	219974	386	Ozone (O3	Mean	ppb	Borough	2	Brooklyn	Summer 20	6/1/2012	33.89	
20	219975	386	Ozone (O3	Mean	ppb	Borough	2	Brooklyn	Summer 20	6/1/2013	31.13	
21	219976	386	Ozone (O3	Mean	ppb	Borough	2	Brooklyn	Summer 20	6/1/2014	31.29	
22	164930	383	Sulfur Diox	Mean	ppb	CD	206	Belmont a	Winter 200	########	5.3	
23	164931	383	Sulfur Diox	Mean	ppb	CD	207	Kingsbridge	Winter 200	########	7.49	
24	130355	639	PM2.5-Att	Estimated	per 100,00	UHF42	101	Kingsbridge	2005-2007	1/1/2005	117.7	
25	130356	639	PM2.5-Att	Estimated	per 100,00	UHF42	102	Northeast	2005-2007	1/1/2005	77.3	
26	130357	639	PM2.5-Att	Estimated	per 100,00	UHF42	103	Fordham -	2005-2007	1/1/2005	67.3	
27	130358	639	PM2.5-Att	Estimated	per 100,00	UHF42	104	Pelham - T	2005-2007	1/1/2005	73.6	
28	130359	639	PM2.5-Att	Estimated	per 100,00	UHF42	105	Crotona -T	2005-2007	1/1/2005	65.8	

VI. Data columns description:

№	Column name	Description	Sample Values
1	Unique ID	Unique Record Identifier is used to marks that one record is unique from any another.	172091, 412533, 667046, 212301 650066.
2	Indicator ID	Identifier of the type of measured value across time and place.	366, 385, 386, 365, 644.
3	Name	Name of the indicator that measured.	NO2, PM2.5, O3, SO2.
4	Measure	How the indicator is measured.	Mean, million miles, Estimated annual rate, Estimated annual rate - children 0 to 17 years old, Estimated annual rate - 18 years old and over.
5	Measure Info	Information (such as units) about the measure.	per 100,000 adults, per km2, per 100,000 children.
6	Geo Type Name	Geography type. For instance, Citywide, Borough, and Community Districts are different geography types. #Offtop: UHF' stands for United Hospital Fund neighborhoods	UHF42, CD, UHF34, Borough, Citywide.
7	Geo Join ID	Identifier of the neighborhood geographic area, used for joining to mapping geography files to make thematic maps.	302, 209, 207, 407, 206.
8	Geo Place Name	Neighborhood name.	West Queens, Downtown - Heights – Slope, Southeast Queens.
9	Time Period	Description of the time that the data applies to; Could be a year, range of years, or season for example.	2005-2007, 2015- 2017, Summer 2012.

10	Start Date	Date value for the start of the time period;	1/1/2005.
		Always a date value; could be useful for	
		plotting a time series.	
11	Data Value	The actual data value for this indicator,	2.8, 2, 2.1, 80, 71.
		measure, place, and time.	
12	Message		Notes that apply to
			the data value; For
			example, if an
			estimate is based
			on small numbers
			we will detail here.

VII. Dataset description:

1. Info about dataset

```
Ввод [5]: airp.info()
                 <class 'pandas.core.frame.DataFrame'>
                RangeIndex: 16122 entries, 0 to 16121
Data columns (total 12 columns):
                  # Column
                                                   Non-Null Count Dtype
                  0 Unique_ID
1 Indicator_ID
2 Name
                                                   16122 non-null
                                                                             int64
                                                   16122 non-null
                                                  16121 non-null object 16122 non-null object object 16121 non-null object 16121 non-null object 16164
                  3 Measure
4 Measure_Info
5 Geo_Type_Name
                  6 Geo_Join_ID
7 Geo_Place_Name
8 Time_Period
                                                   16122 non-null int64
                                                  16122 non-null object
16121 non-null object
                   9 Start_Date
                                                   16121 non-null object
                10 Data Value 16122 non-null flo
11 Message 0 non-null flo
dtypes: float64(2), int64(3), object(7)
                                                   16122 non-null float64
0 non-null float64
                 memory usage: 1.5+ MB
```

2. Info about columns

3. Dataset

Out[18]:		Unique ID	Indicator ID	Name	Measure	Measure Info	Geo Type Name	Geo Join ID	Geo Place Name	Time Period	Start_Date	Data Value	Message
	0	216498	386	Ozone (O3)	Mean	ppb	CD	313	Coney Island (CD13)	Summer 2013	06/01/2013	34.64	Nat
	1	216499	386	Ozone (O3)	Mean	ppb	CD	313	Coney Island (CD13)	Summer 2014	06/01/2014	33.22	Nat
	2	219969	386	Ozone (O3)	Mean	ppb	Borough	1	Bronx	Summer 2013	06/01/2013	31.25	Nal
	3	219970	386	Ozone (O3)	Mean	ppb	Borough	1	Bronx	Summer 2014	06/01/2014	31.15	Nal
	4	164876	383	Sulfur Dioxide (SO2)	Mean	ppb	CD	211	Morris Park and Bronxdale (CD11)	Winter 2008-09	12/01/2008	5.89	Nal
	16117	671118	386	Ozone (O3)	Mean	ppb	CD	306	Park Slope and Carroll Gardens (CD6)	Summer 2020	06/01/2020	28.70	Nat
	16118	671119	386	Ozone (O3)	Mean	ppb	CD	305	East New York and Starrett City (CD5)	Summer 2020	06/01/2020	29.56	Nat
	16119	671120	386	Ozone (O3)	Mean	ppb	CD	304	Bushwick (CD4)	Summer 2020	06/01/2020	29.65	Nat
	16120	671121	386	Ozone (O3)	Mean	ppb	CD	303	Bedford Stuyvesant (CD3)	Summer 2020	06/01/2020	29.28	Nal
	16121	671122	386	Ozone (O3)	Mean	ppb	CD	302	Fort Greene and Brooklyn Heights (CD2)	Summer 2020	06/01/2020	28.93	Naf

VIII. Data Cleaning and Researching:

```
BBOQ [7]: airp = airp.dropna()
airp.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 16118 entries, 0 to 16121
Data columns (total 9 columns):

# Column Non-Null Count Dtype

0 Indicator_ID 16118 non-null int64
1 Name 16118 non-null object
2 Measure 16118 non-null object
3 Geo_Type_Name 16118 non-null object
4 Geo_Join_ID 16118 non-null int64
5 Geo_Place_Name 16118 non-null int64
6 Time_Period 16118 non-null object
7 Start_Date 16118 non-null object
8 Data_Value 16118 non-null float64
dtypes: float64(1), int64(2), object(6)
memory usage: 1.2+ MB
```

```
In [81]: import re
    year_regex = re.compile(r'\d{4}')

def extract_year(row):
    match = year_regex.search(row['Time_Period'])
    if match:
        return match.group()
    else:
        return None

airp['ear'] = airp.apply(extract_year, axis=1)

airp = airp.dropna()
    airp
```

Out	F 0 1 1	٠
out	「orl	٠

	Indicator_ID	Name	Measure	Geo_Type_Name	Geo_Join_ID	Geo_Place_Name	Time_Period	Start_Date	Data_Value	Year
0	386	Ozone (O3)	Mean	CD	313	Coney Island (CD13)	Summer 2013	6/1/2013	34.64	2013
1	386	Ozone (O3)	Mean	CD	313	Coney Island (CD13)	Summer 2014	6/1/2014	33.22	2014
2	386	Ozone (O3)	Mean	Borough	1	Bronx	Summer 2013	6/1/2013	31.25	2013
3	386	Ozone (O3)	Mean	Borough	1	Bronx	Summer 2014	6/1/2014	31.15	2014
4	383	Sulfur Dioxide (SO2)	Mean	CD	211	Morris Park and Bronxdale (CD11)	Winter 2008- 09	12/1/2008	5.89	2008
16117	386	Ozone (O3)	Mean	CD	306	Park Slope and Carroll Gardens (CD8)	Summer 2020	6/1/2020	28.70	2020
16118	386	Ozone (O3)	Mean	CD	305	East New York and Starrett City (CD5)	Summer 2020	6/1/2020	29.56	2020
16119	386	Ozone (O3)	Mean	CD	304	Bushwick (CD4)	Summer 2020	6/1/2020	29.65	2020
16120	386	Ozone (O3)	Mean	CD	303	Bedford Stuyvesant (CD3)	Summer 2020	6/1/2020	29.28	2020
16121	386	Ozone (O3)	Mean	CD	302	Fort Greene and Brooklyn Heights (CD2)	Summer 2020	6/1/2020	28.93	2020

16118 rows × 10 columns

In [83]: airp = airp.drop(columns = "Time_Period")
airp

Out[83]:

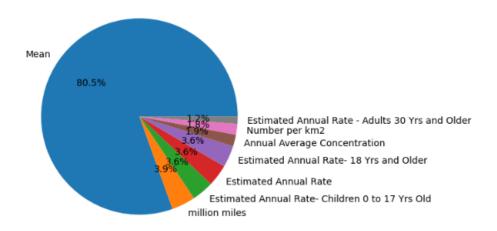
	Indicator_ID	Name	Measure	Geo_Type_Name	Geo_Join_ID	Geo_Place_Name	Start_Date	Data_Value	Year
0	386	Ozone (O3)	Mean	CD	313	Coney Island (CD13)	6/1/2013	34.64	2013
1	386	Ozone (O3)	Mean	CD	313	Coney Island (CD13)	6/1/2014	33.22	2014
2	386	Ozone (O3)	Mean	Borough	1	Bronx	6/1/2013	31.25	2013
3	386	Ozone (O3)	Mean	Borough	1	Bronx	6/1/2014	31.15	2014
4	383	Sulfur Dioxide (SO2)	Mean	CD	211	Morris Park and Bronxdale (CD11)	12/1/2008	5.89	2008
16117	386	Ozone (O3)	Mean	CD	306	Park Slope and Carroll Gardens (CD6)	6/1/2020	28.70	2020
16118	386	Ozone (O3)	Mean	CD	305	East New York and Starrett City (CD5)	6/1/2020	29.56	2020
16119	386	Ozone (O3)	Mean	CD	304	Bushwick (CD4)	6/1/2020	29.65	2020
16120	386	Ozone (O3)	Mean	CD	303	Bedford Stuyvesant (CD3)	6/1/2020	29.28	2020
16121	386	Ozone (O3)	Mean	CD	302	Fort Greene and Brooklyn Heights (CD2)	6/1/2020	28.93	2020

16118 rows × 9 columns

Visualization:

```
In [84]: measure_counts = airp['Measure'].value_counts()
    labels = measure_counts.index
    sizes = measure_counts.values
    fig = plt.figure()
    ax = fig.add_subplot(111)
    ax.pie(sizes, labels=labels, autopct='%1.1f%%')
    ax.set_title('Pie Chart of Measure Counts')
    plt.show()
```

Pie Chart of Measure Counts

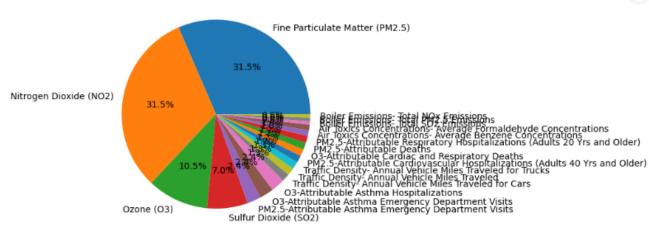


```
In [85]: name_counts = airp["Name"].value_counts()
         name_counts
Out[85]: Fine Particulate Matter (PM2.5)
                                                                                             5076
         Nitrogen Dioxide (NO2)
                                                                                             5075
         Ozone (03)
                                                                                             1692
         Sulfur Dioxide (SO2)
                                                                                             1126
         PM2.5-Attributable Asthma Emergency Department Visits
                                                                                              384
         O3-Attributable Asthma Emergency Department Visits
                                                                                              384
         O3-Attributable Asthma Hospitalizations
                                                                                              384
         Traffic Density- Annual Vehicle Miles Traveled for Cars
                                                                                              213
          Traffic Density- Annual Vehicle Miles Traveled
                                                                                              209
         Traffic Density- Annual Vehicle Miles Traveled for Trucks
                                                                                              209
         PM2.5-Attributable Cardiovascular Hospitalizations (Adults 40 Yrs and Older)
                                                                                              192
         O3-Attributable Cardiac and Respiratory Deaths
                                                                                              192
         PM2.5-Attributable Deaths
                                                                                              192
         PM2.5-Attributable Respiratory Hospitalizations (Adults 20 Yrs and Older)
                                                                                              192
         Air Toxics Concentrations- Average Benzene Concentrations
                                                                                              155
         Air Toxics Concentrations- Average Formaldehyde Concentrations
                                                                                              155
          Boiler Emissions- Total SO2 Emissions
         Boiler Emissions- Total PM2.5 Emissions
Boiler Emissions- Total NOx Emissions
                                                                                               96
                                                                                               96
         Name: Name, dtype: int64
```

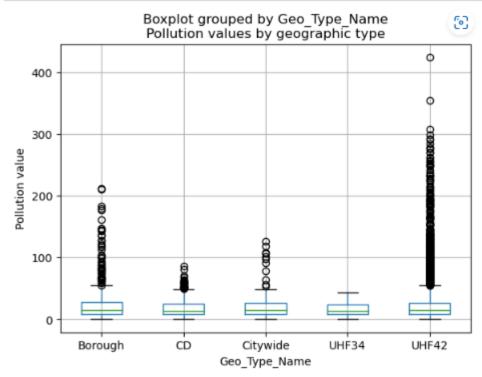
```
In [86]: labels = name_counts.index
    sizes = name_counts.values
    fig = plt.figure()
    ax = fig.add_subplot(111)
    ax.pie(sizes, labels=labels, autopct='%1.1f%%')
    ax.set_title('Pie Chart of Name Counts')
    plt.show()
```

Pie Chart of Name Counts

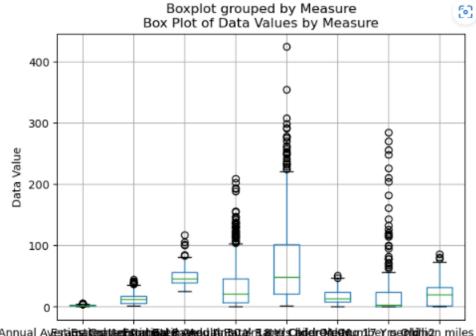




```
In [91]: fig, ax = plt.subplots()
         airp.boxplot(column='Data_Value', by='Geo_Type_Name', ax=ax)
         ax.set_ylabel('Pollution value')
         ax.set_title('Pollution values by geographic type')
         plt.show()
```

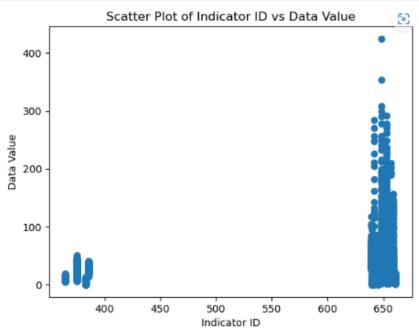


```
In [93]: airp.boxplot(column='Data_Value', by='Measure')
         plt.xlabel('Measure')
         plt.ylabel('Data Value')
         plt.title('Box Plot of Data Values by Measure')
         plt.show()
```



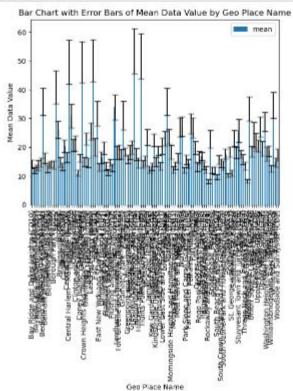
Annual Avæstagsaltenshterfottabilita

```
In [92]: import matplotlib.pyplot as plt
    fig, ax = plt.subplots()
    ax.scatter(airp['Indicator_ID'], airp['Data_Value'])
    ax.set_xlabel('Indicator_ID')
    ax.set_ylabel('Data_Value')
    ax.set_title('Scatter_Plot_of_Indicator_ID_vs_Data_Value')
    plt.show()
```

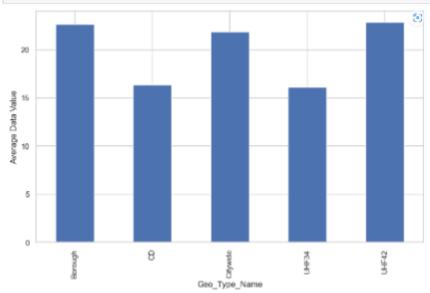


```
In [Si]: place_data = airp.groupby('Goo_Place_Name').agg(('Outa_Value': ['mean', 'sem']))

place_data.plot(kind='bar', y='Outa_Value', yerr='sem', capsize=4)
plt.xlabel('Goo_Place_Name')
plt.ylabel('Mean_Outa_Value')
plt.title('Bar_Chart_with Error_Bars_of_Mean_Outa_Value_by_Goo_Place_Name')
plt.show()
```



```
In [187]: fig, ax = plt.subplots(figsize=(10,6))
airp.groupby("Goo Type Name")["Data Value"].mean().plot(kind="bar", ax=ax)
ax.set_ylabel("Average Data Value")
plt.show()
```

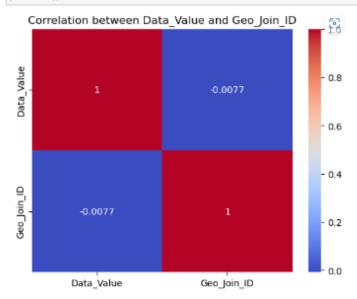


Name: Data_Value, Length: 70, dtype: float64

```
In [94]: mean_by_geo = airp.groupby(['Geo_Type_Name', 'Name'])['Data_Value'].mean()
    print('Mean Data_Value by Geo_Type_Name and Name:\n', mean_by_geo)
```

```
Mean Data_Value by Geo_Type_Name and Name:
Geo_Type_Name Name
               Air Toxics Concentrations- Average Benzene Concentrations
                                                                                                   2.150000
Borough
                Air Toxics Concentrations- Average Formaldehyde Concentrations
                                                                                                   2.610000
                Boiler Emissions- Total NOx Emissions
                                                                                                  46.880000
                Boiler Emissions- Total PM2.5 Emissions
                                                                                                   1.240000
                Boiler Emissions- Total SO2 Emissions
                                                                                                   9.930000
UHF42
                PM2.5-Attributable Respiratory Hospitalizations (Adults 20 Yrs and Older)
                                                                                                  14.855383
                Sulfur Dioxide (SO2)
                                                                                                   2.600476
               Traffic Density- Annual Vehicle Miles Traveled
Traffic Density- Annual Vehicle Miles Traveled for Cars
                                                                                                  29.790476
                                                                                                  27.880723
               Traffic Density- Annual Vehicle Miles Traveled for Trucks
                                                                                                   1.647619
```

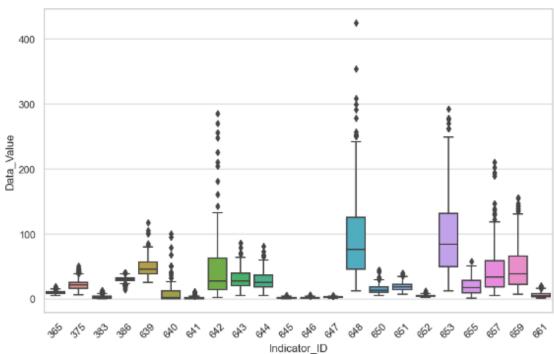
```
In [95]: sns.heatmap(airp[['Data_Value', 'Geo_Join_ID']].corr(), annot=True, cmap='coolwarm')
    plt.title('Correlation between Data_Value and Geo_Join_ID')
    plt.show()
```





Measure

```
In [97]: sns.set(style="whitegrid")
fig, ax = plt.subplots(figsize=(10,6))
sns.boxplot(x="Indicator_ID", y="Data_Value", data=airp, ax=ax)
plt.xticks(rotation=45)
plt.show()
```

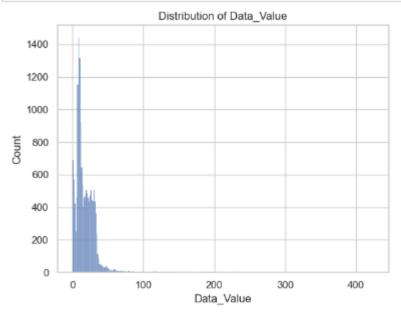


In [98]: airp.info()

<class 'pandas.core.frame.DataFrame'> Int64Index: 16118 entries, 0 to 16121 Data columns (total 9 columns):

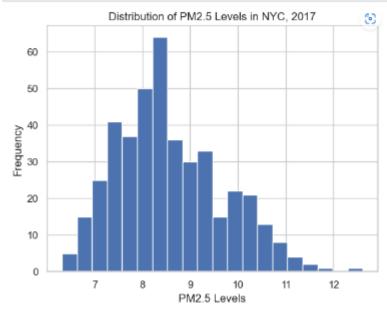
```
# Column
                   Non-Null Count Dtype
                   -----
    Indicator_ID
Θ
                   16118 non-null int64
1
                   16118 non-null object
    Name
    Measure
                   16118 non-null object
    Geo_Type_Name
                   16118 non-null object
    Geo_Join_ID
                   16118 non-null int64
5
    Geo_Place_Name 16118 non-null object
    Start_Date
                   16118 non-null object
    Data_Value
                   16118 non-null float64
8
                   16118 non-null object
    Year
dtypes: float64(1), int64(2), object(6)
memory usage: 1.2+ MB
```

```
In [99]:
sns.histplot(airp['Data_Value'])
plt.title('Distribution of Data_Value')
plt.show()
```

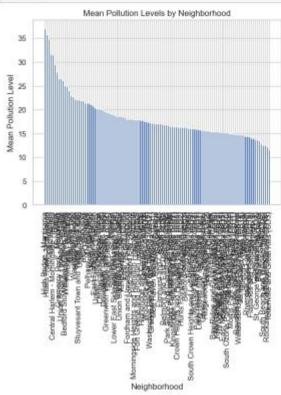


```
In [101]: pm25_2017 = airp[(airp["Name"] == "Fine Particulate Matter (PM2.5)") & (airp["Year"] == "2017")]

plt.hist(pm25_2017["Data_Value"], bins=20)
plt.xlabel("PM2.5 Levels")
plt.ylabel("Frequency")
plt.title("Distribution of PM2.5 Levels in NYC, 2017")
plt.show()
```



```
In [102]: pollution_by_area = airp.groupby('Geo_Place_Name')['Oata_Value'].mean()
pollution_by_area = pollution_by_area.sort_values(ascending-False)
plt.bar(pollution_by_area.index, pollution_by_area.values)
plt.xlabel('Neighborhood')
plt.ylabel('Neighborhood')
plt.title('Nean Pollution Level')
plt.title('Nean Pollution Levels by Neighborhood')
plt.shew()
```



```
In [103]: print("The area with the highest mean pollution level is", pollution_by_area.index[0])
```

The area with the highest mean pollution level is High Bridge - Morrisania

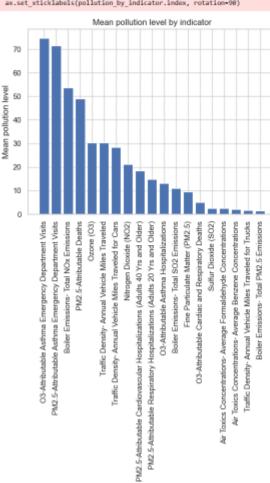
```
In [104]: pollution_by_indicator = airp.groupby('Name')['Data_Value'].mean()
    pollution_by_indicator = pollution_by_indicator.sort_values(ascending=False)
    print(pollution_by_indicator)
```

```
74.718229
03-Attributable Asthma Emergency Department Visits
PM2.5-Attributable Asthma Emergency Department Visits
                                                                                 71.417994
Boiler Emissions- Total NOx Emissions
                                                                                 53.791667
PM2.5-Attributable Deaths
                                                                                 49.116530
                                                                                 30.367398
Ozone (03)
Traffic Density- Annual Vehicle Miles Traveled
                                                                                 30.307177
Traffic Density- Annual Vehicle Miles Traveled for Cars
                                                                                 28.329577
Nitrogen Dioxide (NO2)
                                                                                 21.275992
PM2.5-Attributable Cardiovascular Hospitalizations (Adults 40 Yrs and Older)
                                                                                 18.554893
PM2.5-Attributable Respiratory Hospitalizations (Adults 20 Yrs and Older)
                                                                                 14.865298
O3-Attributable Asthma Hospitalizations
                                                                                 13.119531
Boiler Emissions- Total SO2 Emissions
                                                                                 10.991667
Fine Particulate Matter (PM2.5)
                                                                                 9.516063
O3-Attributable Cardiac and Respiratory Deaths
                                                                                  4.995312
                                                                                 2.614697
Sulfur Dioxide (SO2)
Air Toxics Concentrations- Average Formaldehyde Concentrations
                                                                                 2.481290
Air Toxics Concentrations- Average Benzene Concentrations
                                                                                  2.030201
                                                                                 1.679426
Traffic Density- Annual Vehicle Miles Traveled for Trucks
Boiler Emissions- Total PM2.5 Emissions
                                                                                 1.373958
Name: Data_Value, dtype: float64
```

```
In [105]: fig, ax = plt.subplots()
    ax.bar(pollution by indicator.index, pollution_by_indicator)
    ax.set_xticklabels(pollution_by_indicator.index, rotation=90)
    ax.set_ytlabel('Mean pollution level')
    ax.set_title('Mean pollution level by indicator')
    plt.show()

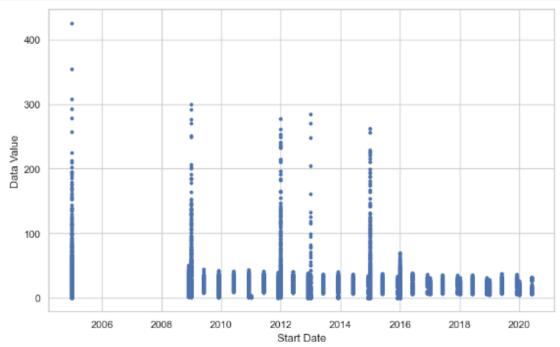
C:\Userslankw\AppQata\Local\Temp\invkernel 2040\1181977917.pv:3: UserWarning: FixedFormatter should only be used together with
```

C:\Users\aakku\AppOata\Local\Temp\ipykernel_2040\i181977917.py:3: UserWarning: FixedFormatter should only be used together with FixedLocator ax.set_xticklabels(pollution_by_indicator.index, rotation=90)



```
In [106]: airp["Start_Date"] = pd.to_datetime(airp["Start_Date"])

fig, ax = plt.subplots(figsize=(10,6))
    ax.scatter(airp["Start_Date"], airp["Data_Value"], s=10)
    ax.set_xlabel("Start_Date")
    ax.set_ylabel("Data_Value")
    plt.show()
```



```
In [109]: data_pivot = airp.pivot_table(index="Indicator_ID", columns="Year", values="Data_Value", aggfunc="mean")
          fig, ax = plt.subplots(figsize=(10,6))
sns.heatmap(data_pivot, cmap="YIGnBu", annot=True, fmt=".2f", linewidths=.5, ax=ax)
          plt.show()
               365
                          13.56 10.83 11.82 10.69 10.34 10.69 9.34 9.09 8.18 8.56 7.93 7.71 6.74
               375
                          30.83 24.93 24.80 22.93 22.06 22.34 20.83 19.94 20.18 19.95 18.40 19.03 14.47
                           5.53 3.72 4.66 2.63 1.63 1.75 0.75 0.27
               383
                                24.76 32.44 31.82 32.92 30.04 30.45 30.91 32.98 28.79 29.92 29.65 29.73
               386
                                                                                                                  100
               639
                                 49.26
                                                  41.74
                                                                     38.56
               640
                                                         14.23
                                                                     7.75
               641
                                                         1.66
                                                                     1.09
                                                                                                                  80
               642
                                                         56.30
               643
                   31.06
                                                                           29.59
            28.95
                                                                           27.71
               645
                     1.70
                                                                           1.66
                                                                                                                  60
               646
                     2.91
                                             1.64
               647
                     3.20
                                             2.16
               648
                    119.69
                                100.22
                                                   91.26
                                                                     12.20
               650
                                 14.44
                                                   12.09
                    20.73
                                                                                                                  - 40
               651 26.15
                                 17.71
                                                   13.37
                                                                     16.99
               652
                    5.09
                                 4.87
                                                   5.14
                                                                     4.89
                                 103.19
                                                                     94.86
               653
                    86.99
                                                   109.46
                                                                                                                 - 20
                     19.53
                                 20.85
               655
                                                                     17.11
                                                   21.82
               657
                                 46.75
                                                   43.89
                                                                     35.51
               659
                     48.41
                                 49.36
                                                   55.87
                                                                     49.60
                     7.51
                                 7.25
                                                   6.81
                                                                     4.07
```

2005 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020 Year

XI. Conclusion

In our project we remove the two columns Unique ID and Message. Check the null value in a row and we write a code how to remove column with null values and replace null values with an average. Then, we experimented with our dataset and see some info about dataset. At the end, we save our changed dataset as a new csv file by the name "Air Pollution".