# ExactSpace Data Science Internship Assessment

```
#Importing necessary libraries for further Analysis
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
df= pd.read_excel("/content/data.xlsx") #Reading the given dataset
```

```
df.head() # Retrieving the first five rows of the DataFrame
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182. |
| **2** | 2017-01-01 | 875.67 | 924.18 | -181.26 | -166.4 |

```
df.shape #Shape of the dataset
```

```
(377719, 7)
```

```
df.loc[104680] #checking the random row values
```

```
time                        2017-12-30 11:20:00
Cyclone_Inlet_Gas_Temp                    878.5
Cyclone_Material_Temp                    949.96
Cyclone_Outlet_Gas_draft                -223.34
Cyclone_cone_draft                      -228.83
Cyclone_Gas_Outlet_Temp                  907.87
Cyclone_Inlet_Draft                     -171.08
Name: 104680, dtype: object
```

# Data Preprocessing

```
df.dtypes #checking the datatypes of the each column
```

```
time                          datetime64[ns]
Cyclone_Inlet_Gas_Temp                object
Cyclone_Material_Temp                 object
Cyclone_Outlet_Gas_draft              object
Cyclone_cone_draft                    object
Cyclone_Gas_Outlet_Temp               object
Cyclone_Inlet_Draft                   object
dtype: object
```

```
type(df.iloc[0,1]), type(df.iloc[377718,4]) #Checking whether all the values(also numerical/float) are Object or Not
```

```
(float, float)
```

```
unique= df[df['Cyclone_Inlet_Gas_Temp'].apply(lambda x: isinstance(x, str))] #Retreiving the rows of Cyclone_Inlet_Gas_Temp consisting the Object datatype
```

```
unique
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_ |
|---|---|---|---|---|---|
| **2471** | 2017-01-09 13:55:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2472** | 2017-01-09 14:00:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2473** | 2017-01-09 14:05:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2474** | 2017-01-09 14:10:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2475** | 2017-01-09 14:15:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **...** | ... | ... | ... | ... | |
| | 2020- | | | | |

```
counts = unique['Cyclone_Inlet_Gas_Temp'].value_counts() #Count of the unique object datatypes in 'Cyclone_Inlet_Gas_Temp'
counts
```

```
Not Connect     723
I/O Timeout     470
Configure       108
Scan Timeout     17
Comm Fail         2
Name: Cyclone_Inlet_Gas_Temp, dtype: int64
```

```
unique['Cyclone_Inlet_Gas_Temp'].unique()
```

```
array(['I/O Timeout', 'Not Connect', 'Scan Timeout', 'Configure',
       'Comm Fail'], dtype=object)
```

```
unique['Cyclone_Outlet_Gas_draft'].unique()
```

```
array(['I/O Timeout', 'Not Connect', 'Scan Timeout', 'Configure',
       'Comm Fail'], dtype=object)
```

```
material_unique= df[df['Cyclone_Material_Temp'].apply(lambda x: isinstance(x, str))] #Retreiving the rows of Cyclone_Material_Temp consisting the Object datatype
```

```
material_unique
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_ |
|---|---|---|---|---|---|
| **2471** | 2017-01-09 13:55:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2472** | 2017-01-09 14:00:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2473** | 2017-01-09 14:05:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2474** | 2017-01-09 14:10:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2475** | 2017-01-09 14:15:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **...** | ... | ... | ... | ... | |
| | 2020- | | | | |

```
counts= material_unique['Cyclone_Material_Temp'].value_counts() #Count of the unique object datatypes in 'Cyclone_Material_Temp'
counts
```

```
Not Connect     723
I/O Timeout     470
Unit Down       271
Configure       108
Scan Timeout     17
Comm Fail         2
Name: Cyclone_Material_Temp, dtype: int64
```

```
outlet_unique = df[df['Cyclone_Outlet_Gas_draft'].apply(lambda x: isinstance(x, str))]  #Retreiving the rows of 'Cyclone_Outlet_Gas_draft' consisting the Object datatype
```

```
outlet_unique
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_ |
|---|---|---|---|---|---|
| **2471** | 2017-01-09 13:55:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2472** | 2017-01-09 14:00:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2473** | 2017-01-09 14:05:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2474** | 2017-01-09 14:10:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2475** | 2017-01-09 14:15:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **...** | ... | ... | ... | ... | |
| | 2020- | | | | |

```
outlet_unique['Cyclone_Outlet_Gas_draft'].value_counts() #Count of the unique object datatypes in 'Cyclone_Outlet_Gas_draft'
```

```
Not Connect     723
I/O Timeout     470
Configure       108
Scan Timeout     17
Comm Fail         2
Unit Down         1
Name: Cyclone_Outlet_Gas_draft, dtype: int64
```

```
cone_unique= df[df['Cyclone_cone_draft'].apply(lambda x: isinstance(x, str))] #Retreiving the rows of 'Cyclone_cone_draft' consisting the Object datatype
cone_unique
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_ |
|---|---|---|---|---|---|
| **2471** | 2017-01-09 13:55:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2472** | 2017-01-09 14:00:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2473** | 2017-01-09 14:05:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |

```
cone_unique['Cyclone_cone_draft'].value_counts() #Count of the unique object datatypes in 'Cyclone_cone_draft'
```

```
Not Connect     723
I/O Timeout     470
Configure       108
Scan Timeout     17
Comm Fail         2
Name: Cyclone_cone_draft, dtype: int64
```

```
gas_unique= df[df['Cyclone_Gas_Outlet_Temp'].apply(lambda x: isinstance(x, str))] #Retreiving the rows of 'Cyclone_Gas_Outlet_Temp' consisting the Object datatype
gas_unique
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_ |
|---|---|---|---|---|---|
| **2471** | 2017-01-09 13:55:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2472** | 2017-01-09 14:00:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2473** | 2017-01-09 14:05:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2474** | 2017-01-09 14:10:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2475** | 2017-01-09 14:15:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **...** | ... | ... | ... | ... | |
| | 2020- | | | | |

```
cone_unique['Cyclone_Gas_Outlet_Temp'].value_counts() #Count of the unique object datatypes in 'Cyclone_cone_draft'
```

```
Not Connect     723
I/O Timeout     470
Configure       108
Scan Timeout     17
Comm Fail         2
Name: Cyclone_Gas_Outlet_Temp, dtype: int64
```

```
inlet_unique= df[df['Cyclone_Inlet_Draft'].apply(lambda x: isinstance(x, str))]  #Retreiving the rows of 'Cyclone_Inlet_Draft' consisting the Object datatype
inlet_unique
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_ |
|---|---|---|---|---|---|
| **2471** | 2017-01-09 13:55:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2472** | 2017-01-09 14:00:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2473** | 2017-01-09 14:05:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2474** | 2017-01-09 14:10:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **2475** | 2017-01-09 14:15:00 | I/O Timeout | I/O Timeout | I/O Timeout | I/O T |
| **...** | ... | ... | ... | ... | |
| | 2020- | | | | |

```
inlet_unique['Cyclone_Inlet_Draft'].value_counts() #Count of the unique object datatypes in 'Cyclone_Inlet_Draft'
```

```
Not Connect     723
I/O Timeout     470
Configure       108
Scan Timeout     17
Unit Down         2
Comm Fail         2
Name: Cyclone_Inlet_Draft, dtype: int64
```

- More than 700 "Not Connect" values, 470 "I/O Timeout" values and 100+ "Configure" values were there in the dataset.
- We have to handle them by replacing by an appropriate values.
- Deleting the rows that consists of "Comm Fail" as it can't impact much in the dataset.

```
df.shape #Checking the shape of the dataframe before data preprocessing
```

```
(377719, 7)
```

```
#Deleting the rows that consists of "Comm Fail"
df1 = df[~df.isin(['Comm Fail']).any(axis=1)]

df1.reset_index(drop=True, inplace=True) # Reset the index if needed
```

```
df1.shape #shape after deleting the two rows
```

```
(377717, 7)
```

Deleted two rows which are not much impactable in dataset.

```
df1.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182. |
| **2** | 2017-01-01 | 875.67 | 924.18 | -181.26 | -166.4 |

```
# Create a copy of the original dataframe
df_copy = df.copy()

# Convert non-numeric values to NaN in the non-datetime columns of the copy
numeric_cols = df_copy.select_dtypes(exclude='datetime').columns
df_copy[numeric_cols] = df_copy[numeric_cols].apply(pd.to_numeric, errors='coerce')
df_copy.reset_index(drop=True, inplace=True)
```

```
df_copy.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 | 875.67 | 924.18 | -181.26 | -166.4 |

```
df_copy.loc[2471] #Checking the row values for a random number '2471'
```

```
time                          2017-01-09 13:55:00
Cyclone_Inlet_Gas_Temp                        NaN
Cyclone_Material_Temp                         NaN
Cyclone_Outlet_Gas_draft                      NaN
Cyclone_cone_draft                            NaN
Cyclone_Gas_Outlet_Temp                       NaN
Cyclone_Inlet_Draft                           NaN
Name: 2471, dtype: object
```

**Observation-1**: All the parameters are NaN values except "Time".

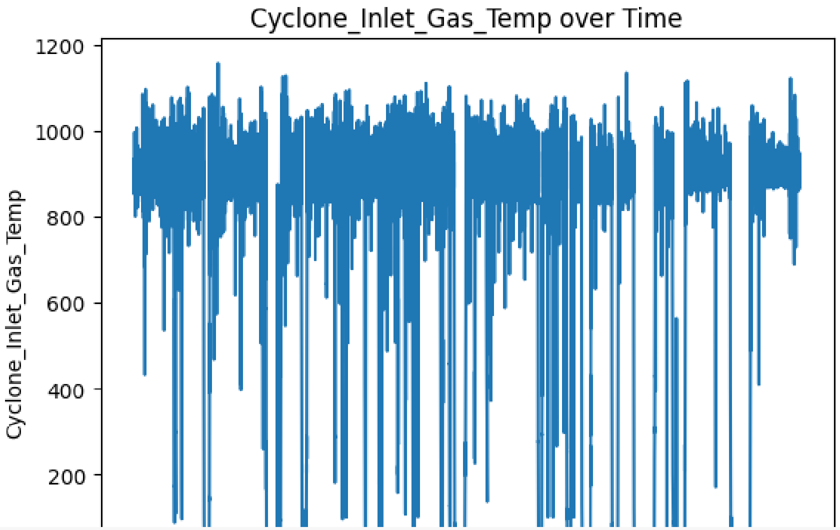
```
df_copy.loc[375585] #Checking the row values for a random number '375585'
```

```
time                          2020-07-31 02:30:00
Cyclone_Inlet_Gas_Temp                     886.18
Cyclone_Material_Temp                         NaN
Cyclone_Outlet_Gas_draft                  -239.29
Cyclone_cone_draft                        -228.77
Cyclone_Gas_Outlet_Temp                    895.48
Cyclone_Inlet_Draft                        -189.0
Name: 375585, dtype: object
```

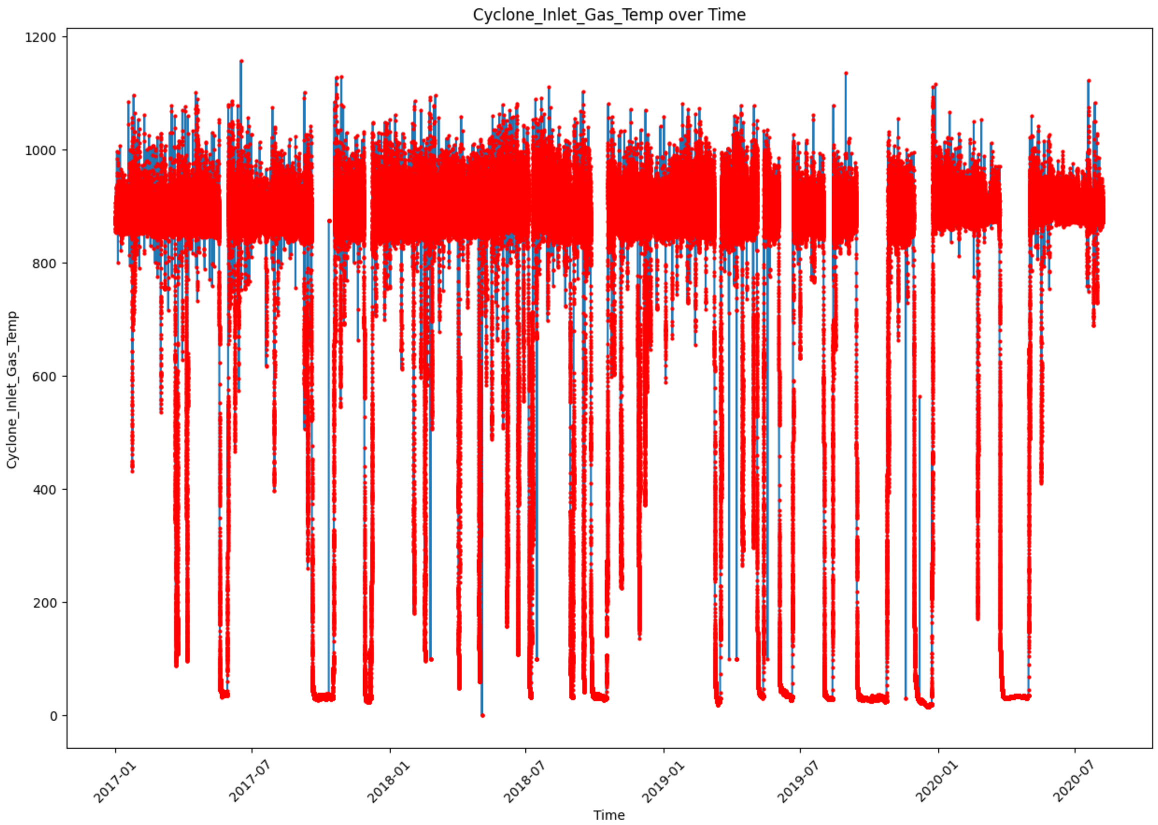
**Observation-2**: All the parameters having a value, except 'Cyclone_Material_Temp'

## Data Visualization for Preprocessing

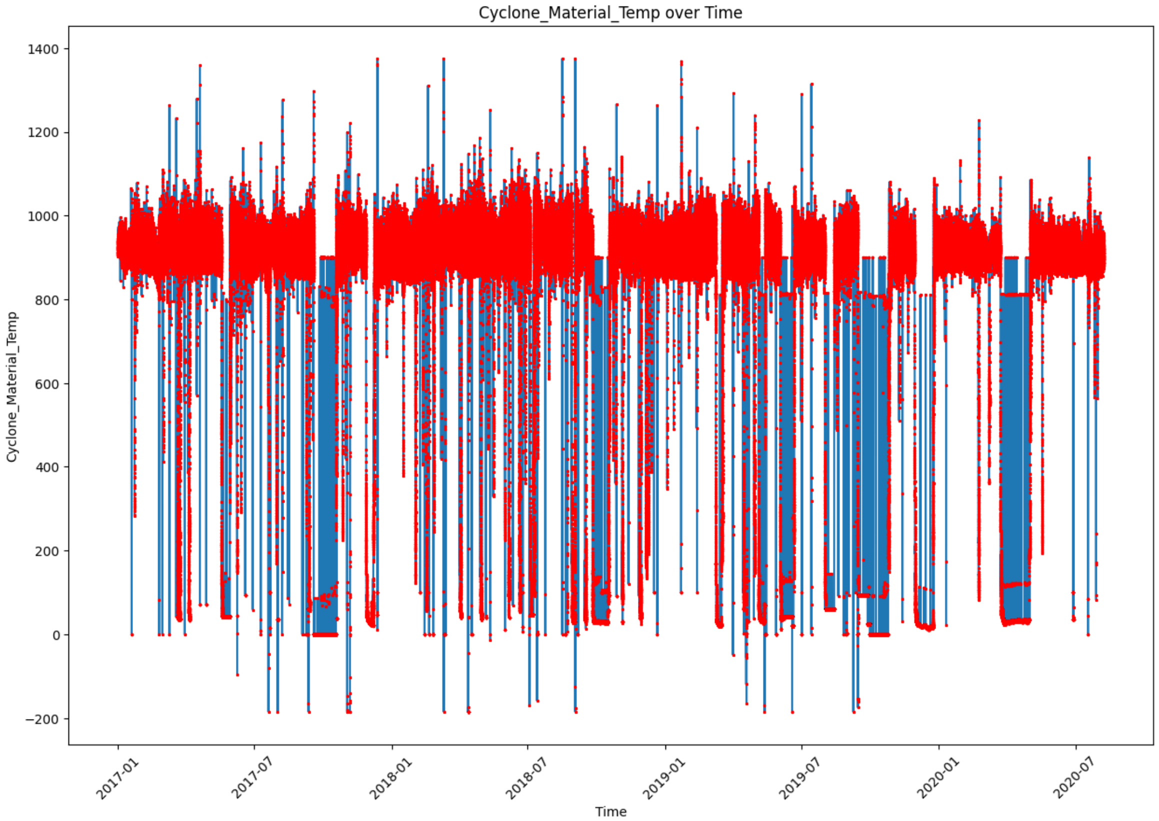
```
mask = pd.to_numeric(df['Cyclone_Inlet_Gas_Temp'], errors='coerce').notnull() #Plotting the graph for 'Cyclone_Inlet_Gas_Temp' feature against 'time'
filtered_df = df.loc[mask]

# Plot the graph
plt.plot(filtered_df['time'], pd.to_numeric(filtered_df['Cyclone_Inlet_Gas_Temp']))
plt.xlabel('Time')
plt.ylabel('Cyclone_Inlet_Gas_Temp')
plt.title('Cyclone_Inlet_Gas_Temp over Time')
plt.xticks(rotation=45)
plt.show()
```




```
df['Cyclone_Inlet_Gas_Temp'] = pd.to_numeric(df['Cyclone_Inlet_Gas_Temp'], errors='coerce') #Plotting the graph for 'Cyclone_Inlet_Gas_Temp' feature against 'time'

plt.figure(figsize=(15, 10))

# Plot the graph with NaN values as gaps
plt.plot(df['time'], df['Cyclone_Inlet_Gas_Temp'])
plt.xlabel('Time')
plt.ylabel('Cyclone_Inlet_Gas_Temp')
plt.title('Cyclone_Inlet_Gas_Temp over Time')
plt.xticks(rotation=45)

# Remove the NaN values from the plot
plt.plot(df['time'], df['Cyclone_Inlet_Gas_Temp'], 'o', markersize=2, color='red')

plt.show()
```




```
df['Cyclone_Material_Temp'] = pd.to_numeric(df['Cyclone_Material_Temp'], errors='coerce') #Plotting the graph for 'Cyclone_Material_Temp' feature against 'time'

plt.figure(figsize=(15, 10))

# Plot the graph with NaN values as gaps
plt.plot(df['time'], df['Cyclone_Material_Temp'])
plt.xlabel('Time')
plt.ylabel('Cyclone_Material_Temp')
plt.title('Cyclone_Material_Temp over Time')
plt.xticks(rotation=45)

# Remove the NaN values from the plot
plt.plot(df['time'], df['Cyclone_Material_Temp'], '*', markersize=2, color='red')

plt.show()
```




## Applying "Interpolation" method for replacing the anomalies

```
columns_to_interpolate = ['Cyclone_Inlet_Gas_Temp', 'Cyclone_Material_Temp', 'Cyclone_Outlet_Gas_draft',
                          'Cyclone_cone_draft', 'Cyclone_Gas_Outlet_Temp', 'Cyclone_Inlet_Draft']
df_interpolated = df_copy.copy() #Copying the 'df_copy' into 'df_interpolated'

# Apply interpolation to the desired columns
df_interpolated[columns_to_interpolate] = df_interpolated[columns_to_interpolate].interpolate(method='linear')

# Verifing the dataset after interpolation
df_interpolated.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 | 875.67 | 924.18 | -181.26 | -166.4 |

```
df_interpolated.loc[2471] #Checking the row '2471' whether all the features were replaced or not
```

```
time                       2017-01-09 13:55:00
Cyclone_Inlet_Gas_Temp              919.701818
Cyclone_Material_Temp               933.643182
Cyclone_Outlet_Gas_draft           -197.345455
Cyclone_cone_draft                 -186.840909
Cyclone_Gas_Outlet_Temp             887.541364
Cyclone_Inlet_Draft                -152.204545
Name: 2471, dtype: object
```

**Observation-3**: As in Observation-1 all the features which were NaN were replaced with Interpolated values.

```
df_interpolated.loc[375585] #Checking the row '375585' whether all the features were replaced or not
```

```
time                       2020-07-31 02:30:00
Cyclone_Inlet_Gas_Temp                  886.18
Cyclone_Material_Temp                  894.115
Cyclone_Outlet_Gas_draft               -239.29
Cyclone_cone_draft                     -228.77
Cyclone_Gas_Outlet_Temp                 895.48
Cyclone_Inlet_Draft                     -189.0
Name: 375585, dtype: object
```

**Observation-4**: As in Observation-2 Cyclone_Material_Temp was NaN is replaced with Interpolated value.

```
df_interpolated.loc[322817]
```

```
time                           2020-01-29 21:10:00
Cyclone_Inlet_Gas_Temp                      878.62
Cyclone_Material_Temp                     896.0025
Cyclone_Outlet_Gas_draft               -276.995833
Cyclone_cone_draft                     -229.004167
Cyclone_Gas_Outlet_Temp                 875.971667
Cyclone_Inlet_Draft                       -226.125
Name: 322817, dtype: object
```

```
df_interpolated.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.04 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.10 |
| **2** | 2017-01-01 | 875.67 | 924.18 | -181.26 | -166.4 |

```
df_interpolated.shape #Checking the shape of the dataset after Interpolation Method
```

```
(377719, 7)
```

```
df_interpolated.to_csv('preprocessed_data.csv', index=True) #Exporting the Preprocessed data for further Analysis
```

```
#Importing Libraries for further Analysis
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from datetime import datetime
```

```
data= pd.read_csv("preprocessed_data.csv")
data = data.drop(data.columns[0], axis=1)
```

```
data.head() #Retreiving the first four rows after preprocessing the data
```

| time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|

```
data['time'] = pd.to_datetime(data['time']) #Checking whether any anomalies(string or object) are present or not
data.dtypes
```

```
time                       datetime64[ns]
Cyclone_Inlet_Gas_Temp            float64
Cyclone_Material_Temp             float64
Cyclone_Outlet_Gas_draft          float64
Cyclone_cone_draft                float64
Cyclone_Gas_Outlet_Temp           float64
Cyclone_Inlet_Draft               float64
dtype: object
```

**Observation-5**: No datatype is present other than Numerical and Datetime for further analysis.

# Feature Engineering

```
data1= data.copy() #Copying the 'data' dataframe to 'data1'
data1.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 | 875.67 | 924.18 | -181.26 | -166.4 |

# Adding day, month and year to obtain further insights

```
data1['day']= data1['time'].dt.day
data1['month']= data1['time'].dt.month
data1['year']= data1['time'].dt.year
```

```
data1.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 | 879.23 | 918.14 | -184.33 | -182.1 |

## Adding 'season' feature

```
data1['time'] = pd.to_datetime(data1['time'])

# Define a function to map months to seasons
def get_season(month):
    if month in [12, 1, 2]: #Months like December, January and February are the Winter Season
        return 'Winter'
    elif month in [6, 7, 8]: #Months like June, July and August are the Monsoon Season
        return 'Rainy'
    else:
        return 'Summer'      #Rest of the months I am considering as Summer

# Apply the function to create the 'season' column
data1['season'] = data1['time'].dt.month.apply(get_season)
```

```
data1.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 00:10:00 | 875.67 | 924.18 | -181.26 | -166.4 |
| **3** | 2017-01-01 00:15:00 | 875.28 | 923.15 | -179.15 | -174.8 |

## Adding 'Week' number for observation on weekly basis

```
data1['weekday'] = data1['time'].dt.day_name()
```

```
data1.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 00:10:00 | 875.67 | 924.18 | -181.26 | -166.4 |
| **3** | 2017-01-01 00:15:00 | 875.28 | 923.15 | -179.15 | -174.8 |
| **4** | 2017-01-01 00:20:00 | 891.66 | 934.26 | -178.32 | -173.7 |

```
data1.columns
```

```
Index(['time', 'Cyclone_Inlet_Gas_Temp', 'Cyclone_Material_Temp',
       'Cyclone_Outlet_Gas_draft', 'Cyclone_cone_draft',
       'Cyclone_Gas_Outlet_Temp', 'Cyclone_Inlet_Draft', 'day', 'month',
       'year', 'season', 'weekday'],
      dtype='object')
```

## Cyclic Features

```
data1['hour_of_day'] = data1['time'].dt.hour
data1['day_of_year'] = data1['time'].dt.dayofyear
```

```
data1.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 00:10:00 | 875.67 | 924.18 | -181.26 | -166.4 |
| **3** | 01-01 | 875.28 | 923.15 | -179.15 | -174.8 |

```
data1['date'] = data1['time'].dt.date
```

```
data1.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 00:10:00 | 875.67 | 924.18 | -181.26 | -166.4 |
| **3** | 2017-01-01 00:15:00 | 875.28 | 923.15 | -179.15 | -174.8 |
| **4** | 2017-01-01 00:20:00 | 891.66 | 934.26 | -178.32 | -173.7 |

```
data1['Time'] = data1['time'].dt.strftime('%H:%M')
```

```
data1.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 00:10:00 | 875.67 | 924.18 | -181.26 | -166.4 |
| | 2017- | | | | |

```
data1.columns
```

```
Index(['time', 'Cyclone_Inlet_Gas_Temp', 'Cyclone_Material_Temp',
       'Cyclone_Outlet_Gas_draft', 'Cyclone_cone_draft',
       'Cyclone_Gas_Outlet_Temp', 'Cyclone_Inlet_Draft', 'day', 'month',
       'year', 'season', 'weekday', 'hour_of_day', 'day_of_year', 'date',
       'Time'],
      dtype='object')
```

## Adding "time_category" column consists (morning, afternoon, evening and night)

```
def get_time_category(time):
    hour = time.hour
    if 5 <= hour < 12:
        return 'Morning'
    elif 12 <= hour < 17:
        return 'Afternoon'
    elif 17 <= hour < 21:
        return 'Evening'
    else:
        return 'Night'

# Convert 'time' column to datetime type
data['time'] = pd.to_datetime(data['time'])

# Apply the function to create the 'time_category' column
data['time_category'] = data['time'].apply(get_time_category)
```

```
data.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2017-01-01 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2017-01-01 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2017-01-01 00:10:00 | 875.67 | 924.18 | -181.26 | -166.4 |
| **3** | 2017-01-01 00:15:00 | 875.28 | 923.15 | -179.15 | -174.8 |
| | 2017- | | | | |

## Data Visualization

### Outlier Detection

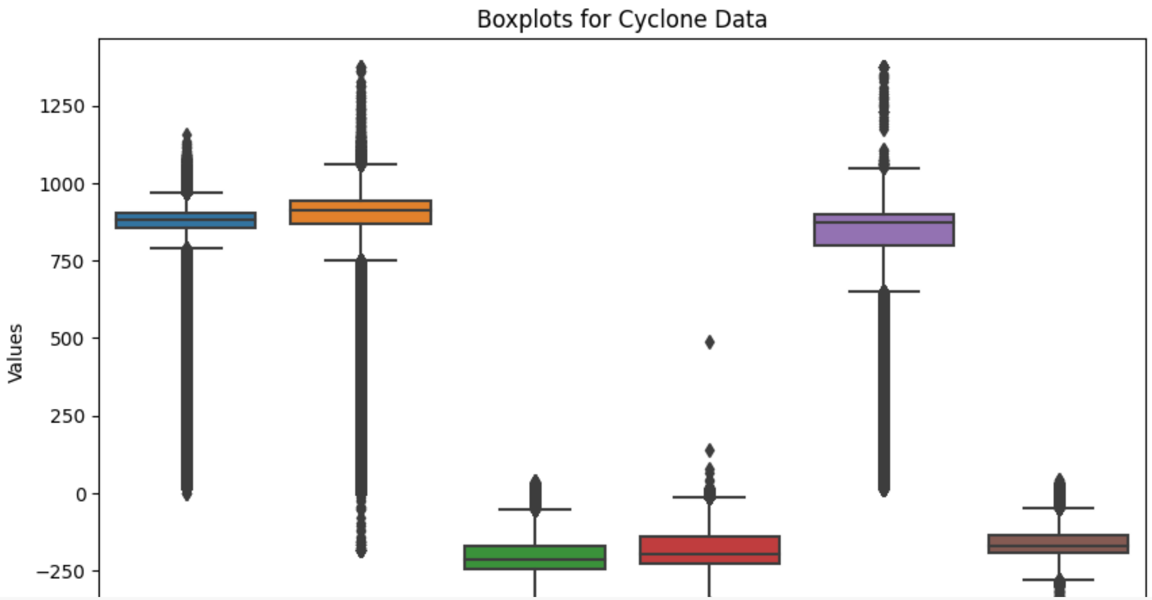
```
data.head()
```

| | time | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draf |
|---|---|---|---|---|---|
| **0** | 2023-06-18 00:00:00 | 867.63 | 910.42 | -189.54 | -186.0 |
| **1** | 2023-06-18 00:05:00 | 879.23 | 918.14 | -184.33 | -182.1 |
| **2** | 2023-06-18 00:10:00 | 875.67 | 924.18 | -181.26 | -166.4 |
| **3** | 2023-06-18 00:15:00 | 875.28 | 923.15 | -179.15 | -174.8 |
| **4** | 2023-06-18 00:20:00 | 891.66 | 934.26 | -178.32 | -173.7 |

```
data.columns
```

```
     Index(['time', 'Cyclone_Inlet_Gas_Temp', 'Cyclone_Material_Temp',
            'Cyclone_Outlet_Gas_draft', 'Cyclone_cone_draft',
            'Cyclone_Gas_Outlet_Temp', 'Cyclone_Inlet_Draft', 'day', 'month',
            'year', 'season', 'weekday', 'hour_of_day', 'day_of_year', 'date',
            'Time', 'time_category'],
           dtype='object')
```

```
import seaborn as sns
subset_data = data[['Cyclone_Inlet_Gas_Temp', 'Cyclone_Material_Temp',
                   'Cyclone_Outlet_Gas_draft', 'Cyclone_cone_draft',
                   'Cyclone_Gas_Outlet_Temp', 'Cyclone_Inlet_Draft']]

# Reshape the DataFrame for plotting
melted_data = pd.melt(subset_data)

# Set the figure size
plt.figure(figsize=(10, 6))

# Create boxplots using seaborn
sns.boxplot(x='variable', y='value', data=melted_data)

# Set labels and title
plt.xlabel('Columns')
plt.ylabel('Values')
plt.title('Boxplots for Cyclone Data')

# Rotate x-axis labels for better visibility
plt.xticks(rotation=90)

# Show the plot
plt.show()
```




```
subset_data.describe().round(2)
```

| | Cyclone_Inlet_Gas_Temp | Cyclone_Material_Temp | Cyclone_Outlet_Gas_draft | Cyclone_cone_draft | Cy( |
|---|---|---|---|---|---|
| **count** | 377719.00 | 377719.00 | 377719.00 | 377719.00 | |
| **mean** | 726.03 | 749.40 | -177.45 | -164.25 | |
| **std** | 329.75 | 352.07 | 99.38 | 90.31 | |
| **min** | 0.00 | -185.00 | -456.66 | -459.31 | |
| **25%** | 855.88 | 867.07 | -247.15 | -226.73 | |
| **50%** | 882.32 | 913.23 | -215.08 | -198.43 | |
| **75%** | 901.08 | 943.58 | -169.25 | -142.37 | |
| **max** | 1157.63 | 1375.00 | 40.27 | 488.86 | |

```
for column in subset_data.columns:
    # Calculate the lower and upper whiskers
    whiskers = data[column].describe()[['25%', '75%']].values
    iqr = whiskers[1] - whiskers[0]
    lower_whisker = whiskers[0] - 1.5 * iqr
    upper_whisker = whiskers[1] + 1.5 * iqr

    # Count the values outside minima and maxima
    count_below_minima = (data[column] < lower_whisker).sum()
    count_above_maxima = (data[column] > upper_whisker).sum()
```

```
print("Column:", column)
print("Values below minima:", count_below_minima)
print("Values above maxima:", count_above_maxima)
print()
```

```
Column: Cyclone_Inlet_Gas_Temp
Values below minima: 81914
Values above maxima: 3919

Column: Cyclone_Material_Temp
Values below minima: 79169
Values above maxima: 639

Column: Cyclone_Outlet_Gas_draft
Values below minima: 30
Values above maxima: 81993

Column: Cyclone_cone_draft
Values below minima: 20
Values above maxima: 75235

Column: Cyclone_Gas_Outlet_Temp
Values below minima: 80644
Values above maxima: 118

Column: Cyclone_Inlet_Draft
Values below minima: 127
Values above maxima: 82364
```

## Obtaining Insights

Power BI was utilized to visualize the most crucial insights, as it proved to be a versatile and efficient tool compared to Python. Its capabilities enabled us to obtain a comprehensive and detailed understanding of the data, revealing numerous valuable insights. The visualizations created in Power BI facilitated a more thorough analysis and interpretation of the data, leading to a deeper exploration of the underlying patterns and trends.

I have shared with you the PowerBI file, specifically named 'ExactSpace_Assessment,' in which I have extensively worked on the Data Visualization and Insights part.