BEGINNER LEVEL

MATPLOTLIB AND PANDAS

Overview of Matplotlib:

→Matplotlib is a widely-used Python library for creating static, interactive, and animated visualizations. It provides a comprehensive environment for creating a wide variety of plots and graphs.

→Matplotlib is highly customizable and is often used in conjunction with other libraries like NumPy and Pandas for handling and visualizing data. It serves as the foundation for many higher-level plotting libraries, such as Seaborn and Plotly.

→Matplotlib is a powerful plotting library in Python used for creating static, animated, and interactive visualizations.

→Matplotlib's primary purpose is to provide users with the tools and functionality to represent data graphically, making it easier to analyze and understand.

→It was originally developed by John D. Hunter in 2003 and is now maintained by a large community of developers.

→Matplotlib is a comprehensive library for creating static, animated, and interactive plots in Python.

→It provides flexibility for visualizing data in multiple formats such as line charts, bar plots, histograms, pie charts, and scatter plots.

→Primary Module: pyplot is the most used module in Matplotlib for easy plotting, functioning similarly to MATLAB.

Key Features of Matplotlib

- **Highly Customizable:** Control every element of a plot (titles, axes, legends, ticks, etc.).
- **Supports Multiple Plot Types:** Includes line plots, scatter plots, bar charts, histograms, pie charts, and more.
- **Interactive and Animated Plots:** Supports toolkits like mpl_toolkits for 3D plots and interactive backends for notebooks.
- **Integration:** Works seamlessly with other libraries such as Pandas and NumPy.

Why and When should choose Matplotlib for Data Visualization?

Matplotlib is popular due to its ease of use, extensive documentation, and wide range of plotting capabilities. It offers flexibility in customization, supports various plot types, and integrates well with other Python libraries like NumPy and Pandas.

Matplotlib is a suitable choice for various data visualization tasks, including exploratory data analysis, scientific plotting, and creating publication-quality plots. It excels in scenarios where users require fine-grained control over plot customization and need to create complex or specialized visualizations.

Advantages of Matplotlib

Matplotlib is a widely used plotting library in Python that provides a variety of plotting tools and capabilities:

1. **Versatility**: Matplotlib can create a wide range of plots, including line plots, scatter plots, bar plots, histograms, pie charts, and more.
2. **Customization**: It offers extensive customization options to control every aspect of the plot, such as line styles, colors, markers, labels, and annotations.
3. **Integration with NumPy**: Matplotlib integrates seamlessly with NumPy, making it easy to plot data arrays directly.
4. **Publication Quality**: Matplotlib produces high-quality plots suitable for publication with fine-grained control over the plot aesthetics.

Disadvantages of Matplotlib

While Matplotlib is a powerful and versatile plotting library, it also has some disadvantages that users might encounter:

1. **Steep Learning Curve**: For beginners, Matplotlib can have a steep learning curve due to its extensive customization options and sometimes complex syntax.
2. **Verbose Syntax**: Matplotlib's syntax can be verbose and less intuitive compared to other plotting libraries like Seaborn or Plotly, making it more time-consuming to create and customize plots.
3. **Default Aesthetics**: The default plot aesthetics in Matplotlib are often considered less visually appealing compared to other libraries, requiring more effort to make plots visually attractive.

4. **Limited Interactivity**: While Matplotlib does support interactive plotting to some extent, it does not offer as many interactive features and options as other libraries like Plotly.

Library Overview:

1.Core Module: pyplot, which offers functions to create different types of plots.

2.Customization: Supports customization of labels, axes, titles, and legend positioning.

3. Integration: Works well with Jupyter notebooks and other interactive environments.

4.Performance: Suitable for creating detailed, publication-quality plots.

Common Use Cases:

1.Data exploration

2. Publishing static visualizations

3.Customizing plots for more granular control

Different Types of Graph in Matplotlib:

Matplotlib offers a wide range of plot types to suit various data visualization needs. Here are some of the most commonly used types of plots in Matplotlib:

- Line Graph
- Stem Plot
- Bar chart
- Histograms
- Scatter Plot
- Stack Plot
- Box Plot
- Pie Chart
- Error Plot
- Violin Plot
- 3D Plots

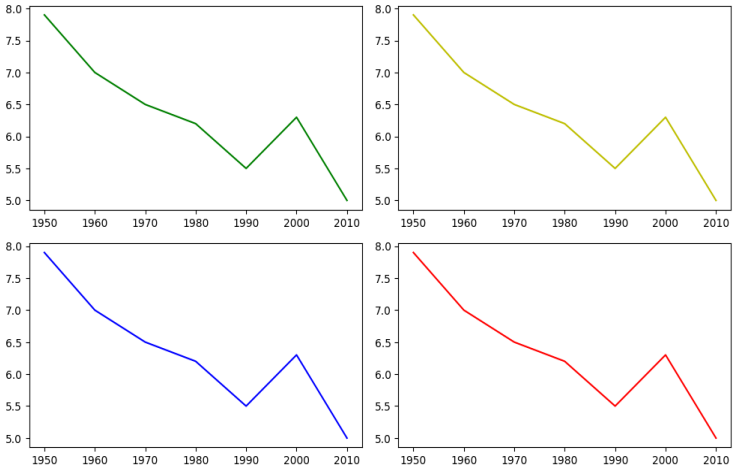
1. Line Plot

- **Use Case:** Showing trends or changes over time.
- **How it works:** Plots data points connected by straight lines.

Example:

```
import matplotlib.pyplot as plt

x = [1, 2, 3, 4] y = [10, 20, 15,

30] plt.plot(x, y, marker='o')

plt.title("Line Plot") plt.show()
```

Output:



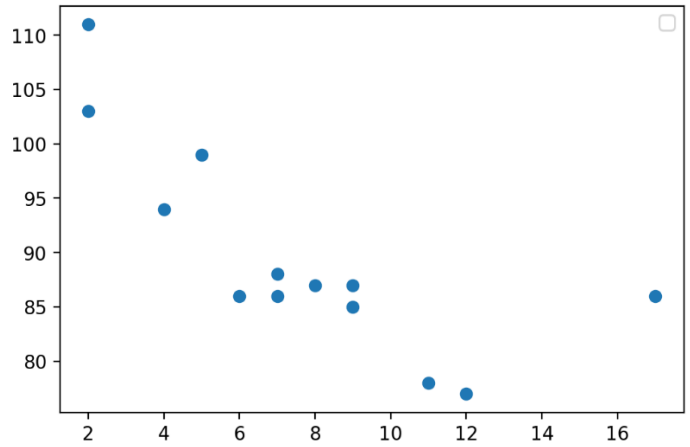
2. Scatter Plot

- **Use Case:** Displaying relationships between two variables.
- **How it works:** Plots individual data points without connecting them.

Example:

```
X=np.array([5,7,8,7,2,17,2,9,4,11,1
2,9,6])

Y=np.array([99,86,87,88,111,86,10
3,87,94,78,77,85,86])

plt.scatter(x, y)

plt.legend()

plt.show()
```

Output:



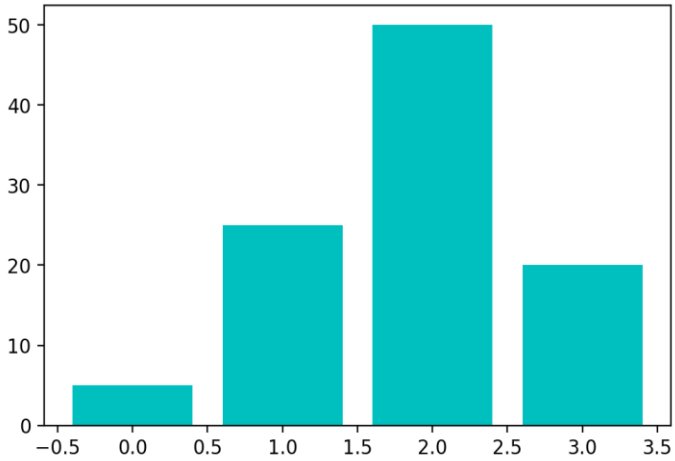
3. Bar Plot

- **Use Case:** Comparing discrete categories.
- **How it works:** Uses rectangular bars to represent data values.

Example:

```
#define array
data= [5. , 25. , 50. , 20.]
plt.bar(range(len(data)), data,color='c')
plt.show()
```

Output:



4. Histogram

- **Use Case:** Showing frequency distributions.
- **How it works:** Groups data into bins and shows the count of items in each bin.

Example:

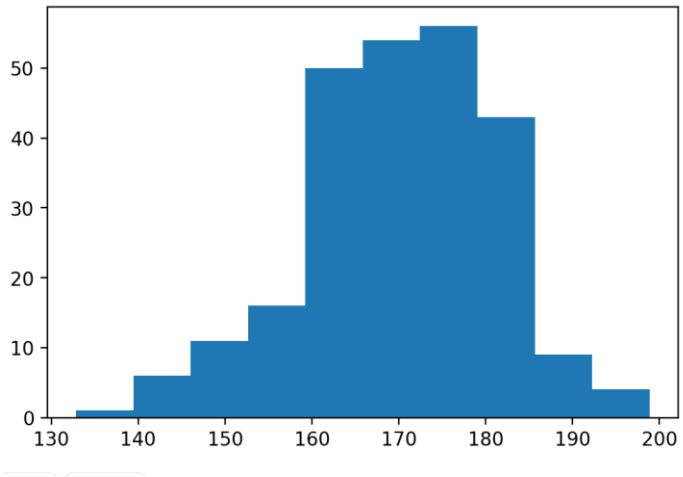
#draw random samples from random distributions.

x = np.random.normal(170, 10, 250)

#plot histograms

plt.hist(x) plt.show()

Output:



5. Pie Chart

- **Use Case:** Showing proportions of a whole.
- **How it works:** Displays data as a circle divided into slices.

Example:

#define the figure size

plt.figure(figsize=(7,7))

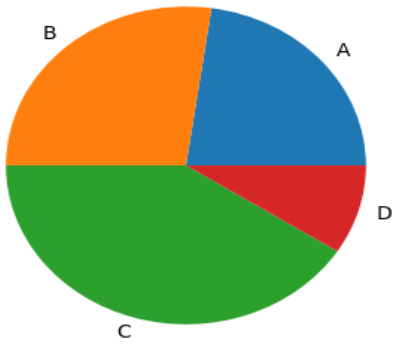
x = [25,30,45,10]

#labels of the pie chart

labels = ['A','B','C','D']

```
plt.pie(x, labels=labels)
plt.show()
```

Output:



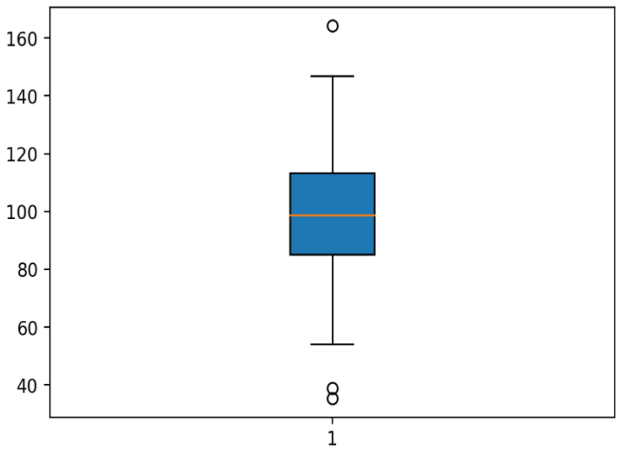
6. Box Plot (or Whisker Plot)

- **Use Case:** Summarizing data distribution and detecting outliers.
- **How it works:** Shows quartiles, medians, and outliers of a dataset.

Example:

```
#create the random values by using numpy
values= np.random.normal(100, 20, 300)
#creating the plot by boxplot() function which is avilable in matplotlib
plt.boxplot(values,patch_artist=True,vert=True)
plt.show()
```

Output:



7. Heatmap

- **Use Case:** Visualizing matrix-like data (e.g., correlations).
- **How it works:** Displays values as color-shaded cells.

Example:

```
import numpy as np data =
np.random.rand(3, 3)
plt.imshow(data, cmap='hot', interpolation='nearest')
plt.title("Heatmap") plt.show()
```

8. Stacked Bar Plot

- **Use Case:** Comparing parts of different categories.
- **How it works:** Stacks multiple bars in a single bar

Example:

```
x = ['A', 'B', 'C']
y1 = [5, 7, 3] y2
= [3, 8, 5]
plt.bar(x, y1, label='Set 1') plt.bar(x,
y2, bottom=y1, label='Set 2')
plt.legend()
plt.title("Stacked Bar Plot") plt.show()
```

9. Area Plot

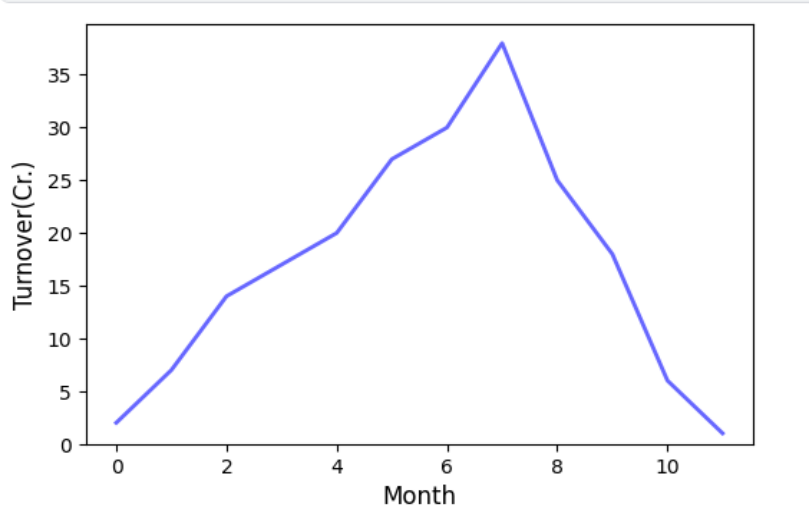
- **Use Case:** Similar to line plots, but emphasizes the magnitude under the line.
- **How it works:** Fills the area below the line plot.

Example:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
y = [2, 7, 14, 17, 20, 27, 30, 38,
25, 18, 6, 1]

plt.plot(np.arange(12),y,
color="blue", alpha=0.6,
linewidth=2)

plt.xlabel('Month', size=12)

plt.ylabel('Turnover(Cr.)', size=12)

plt.ylim(bottom=0)

plt.show()
```

Output:



10.3D Graph

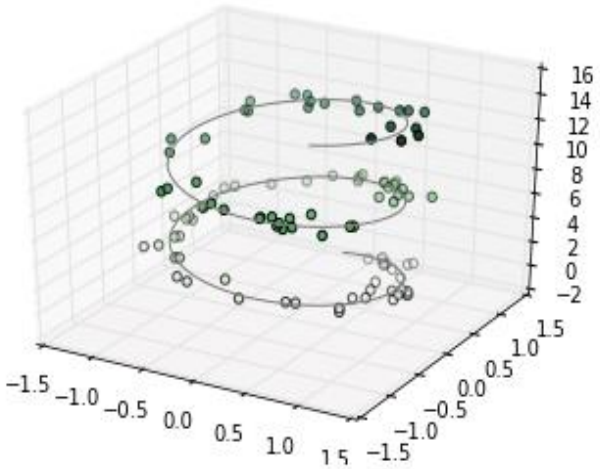
Now that you have seen some simple graphs, it's time to check some complex ones, i.e., 3-D graphs. Initially, Matplotlib was built for 2-dimensional graphs, but later, 3-D graphs were added. Let's check how you can plot a 3-D graph in Matplotlib.

Example:

```
ax = plt.axes(projection='3d')

# Data for a three-dimensional line

zline = np.linspace(0, 15, 1000)

xline = np.sin(zline)

yline = np.cos(zline)

ax.plot3D(xline, yline, zline, 'gray')
```

```
# Data for three-dimensional scattered points
zdata = 15 * np.random.random(100)
xdata = np.sin(zdata) + 0.1 *
np.random.randn(100)
ydata = np.cos(zdata) + 0.1 *
np.random.randn(100)
ax.scatter3D(xdata, ydata, zdata, c=zdata,
cmap='Greens');
```

Output:



Resources:

Official Matplotlib Documentation

Matplotlib Tutorial (Python Graphing)

Matplotlib Examples and Tutorials

Overview of Pandas:

→Pandas is a powerful data analysis and manipulation library for Python.

→It primarily handles structured data (such as dataframes) and offers tools for cleaning, transforming, and analyzing data efficiently.

→While it is not primarily a plotting library, Pandas integrates with Matplotlib to quickly generate plots from dataframes, making it ideal for exploratory data analysis (EDA).

→Pandas is an open-source data analysis and manipulation tool, highly regarded for its ease of use and flexibility.

→It is built on top of the Python programming language and offers powerful data structures for efficiently handling and analyzing large datasets.

→pandas (styled as pandas) is a software library written for the Python programming language for data manipulation and analysis.

→In particular, it offers data structures and operations for manipulating numerical tables and time series.

→It is free software released under the three-clause BSD license.

Key Features of Pandas

Pandas provides several key features that make it an indispensable tool for data scientists and analysts working with Python:

- **Handling of Missing Data**: Pandas is adept at handling missing data and provides mechanisms for representing data as NaN, NA, or NaT without compromising the dataset's integrity.
- **Size Mutability**: It allows for dynamic modification of data structures, enabling the insertion and deletion of columns in DataFrames.
- **Data Alignment**: Pandas can automatically align data in computations or allow users to explicitly align datasets to a set of labels.
- **Group By Functionality**: It offers robust capabilities for performing splitapply-combine operations on datasets, which is essential for both aggregating and transforming data.
- **Data Conversion**: The library simplifies the conversion of disparate data types into uniform DataFrames.
- **Data Slicing and Indexing**: Pandas provides intuitive methods for slicing, indexing, and subsetting large datasets.

What is Pandas Library in Python?

Pandas is a powerful and versatile library that simplifies the tasks of data manipulation in Python. Pandas is well-suited for working with tabular data, such as spreadsheets or SQL tables.

The Pandas library is an essential tool for data analysts, scientists, and engineers working with structured data in Python.

What is Python Pandas used for?

The Pandas library is generally used for data science, but have you wondered why? This is because the Pandas library is used in conjunction with other libraries that are used for data science.

It is built on top of the **NumPy library** which means that a lot of the structures of NumPy are used or replicated in Pandas.

The data produced by Pandas is often used as input for plotting functions in **Matplotlib**, statistical analysis in **SciPy**, and machine learning algorithms in **Scikit-learn**.

You must be wondering, Why should you use the Pandas Library. Python's Pandas library is the best tool to analyze, clean, and manipulate data.

Here is a list of things that we can do using Pandas.

- Data set cleaning, merging, and joining.
- Easy handling of missing data (represented as NaN) in floating point as well as non-floating point data.
- Columns can be inserted and deleted from DataFrame and higherdimensional objects.
- Powerful group by functionality for performing split-apply-combine operations on data sets.

Library Overview:

1.Data Frame: Two-dimensional, size-mutable, and heterogeneous tabular data structure.

2.Series: One-dimensional array-like object that can hold any data type.

3.Data Handling: Offers a rich set of functions for data manipulation, such as filtering, grouping, and aggregating.

4.Integration: Can generate simple plots using .plot() methods that leverage Matplotlib behind the scenes.

Common Use Cases:

1.Data cleaning and preparation

2.Fast exploratory data analysis (EDA)

3.Generating simple plots directly from Data Frames

Advantages of Pandas

1. Easy-to-Use Data Structures
2. Data Handling and Cleaning
3. Flexible Input and Output
4. Fast and Efficient
5. Powerful Data Aggregation and Grouping
6. Time Series Support
7. Visualization
8. Community Support and Documentation

Disadvantages of Pandas

1. Performance Issues with Large Datasets
2. Memory Consumption
3. Steep Learning Curve for Beginners
4. Inconsistent Performance in Some Operations
5. Chained Indexing Issues
6. Limited Parallelization Support
7. Error Handling Can Be Tricky

Resources:

Official Pandas Documentation

Pandas Plotting Documentation

Pandas Quick Start Guide

Different types of Graph in Pandas:

1. Line Plot
2. Bar Plot (Vertical and Horizontal)
3. Scatter Plot
4. Histogram
5. Pie Chart
6. Box Plot (Whisker Plot)
7. Area Plot
8. Hexbin Plot
9. Density Plot (KDE)
10. Multiple Subplots
11. Stacked Bar Plot
12. Lag Plot

1. Line Plot

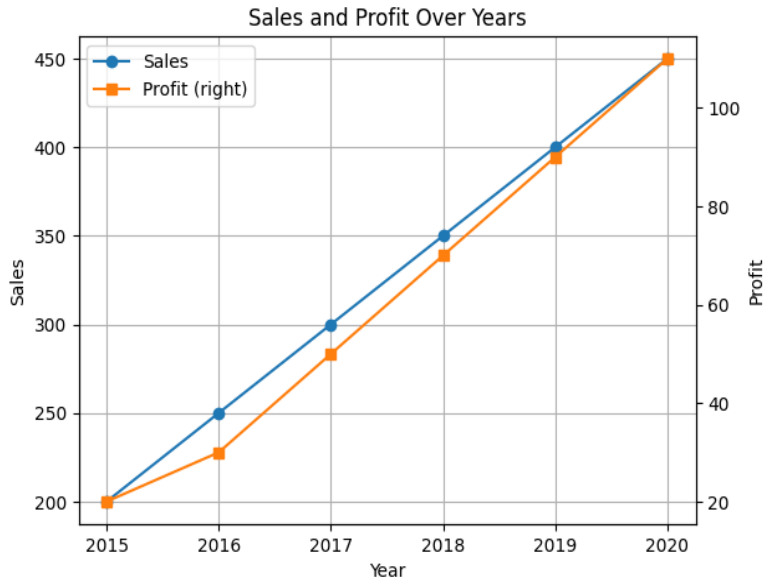
- **Use Case:** Showing trends over time or sequential data.
- **Method:** plot.line()

Example

```
import pandas as pd
import matplotlib.pyplot as plt
data = {
    'Year': [2015, 2016, 2017, 2018, 2019, 2020],
    'Sales': [200, 250, 300, 350, 400, 450],
    'Profit': [20, 30, 50, 70, 90, 110]
}
df = pd.DataFrame(data)
```

```
ax = df.plot(x='Year', y='Sales', kind='line', marker='o', title='Sales and
Profit Over Years')
df.plot(x='Year', y='Profit', kind='line', marker='s', ax=ax,
secondary_y=True)
ax.set_ylabel('Sales')
ax.right_ax.set_ylabel('Profit')
ax.grid(True)
plt.show()
```

Output:



2. Bar Plot (Vertical and Horizontal)

- **Use Case:** Comparing categorical data.

Vertical Bar Plot:

```
df.plot(x='Year', y='Sales', kind='bar', title='Sales by Year')
```

Horizontal Bar Plot:

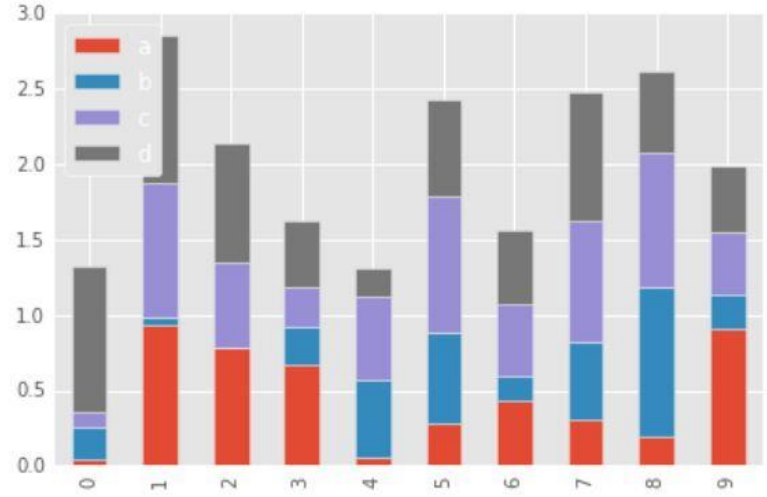
```
df.plot(x='Year', y='Sales', kind='barh', title='Sales by Year (Horizontal)')
```

Example:

```
df.plot.bar(stacked=True)
```

Output:

```
<matplotlib.axes._subplots.AxesSubplot at 0x12657bb38>
```



3. Scatter Plot

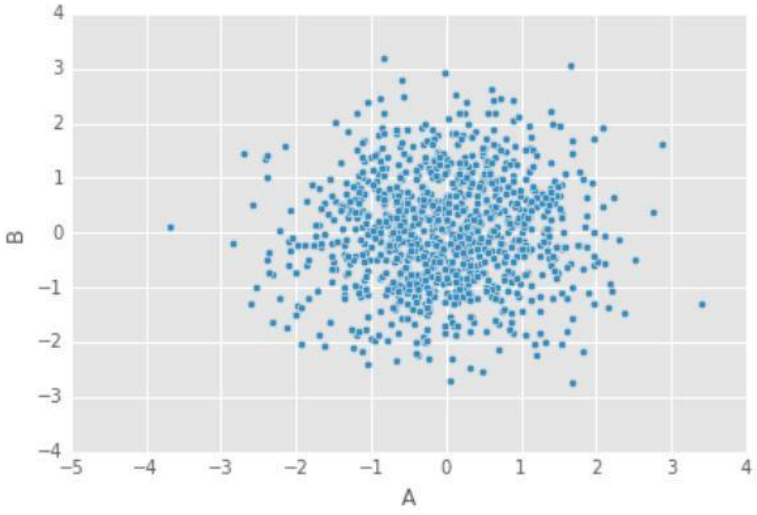
- **Use Case:** Visualizing relationships between two variables.
- **Method:** plot.scatter()

Example

df.plot.scatter(x='A', y='B')

Output:

```
<matplotlib.axes._subplots.AxesSubplot at 0x126b90fd0>
```



4. Histogram

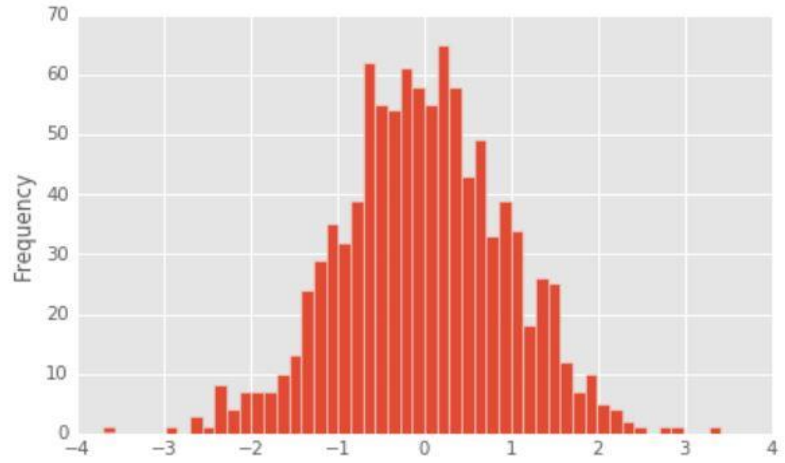
- **Use Case:** Displaying the frequency distribution of a dataset.
- **Method:** plot.hist()

Example

```
data = pd.Series([1, 2, 2, 3, 3, 3, 4, 5, 5, 6])
data.plot(kind='hist', bins=5, title='Histogram of Values')
```

Output:

```
<matplotlib.axes._subplots.AxesSubplot at 0x12685e9b0>
```



5. Pie Chart

- **Use Case:** Showing proportions of a whole.
- **Method:** plot.pie()

Example

```
data = pd.Series([30, 40, 20, 10],
index=['A', 'B', 'C', 'D'])
data.plot(kind='pie', autopct='%1.1f%%', title='Category Distribution')
```

6. Box Plot (Whisker Plot)

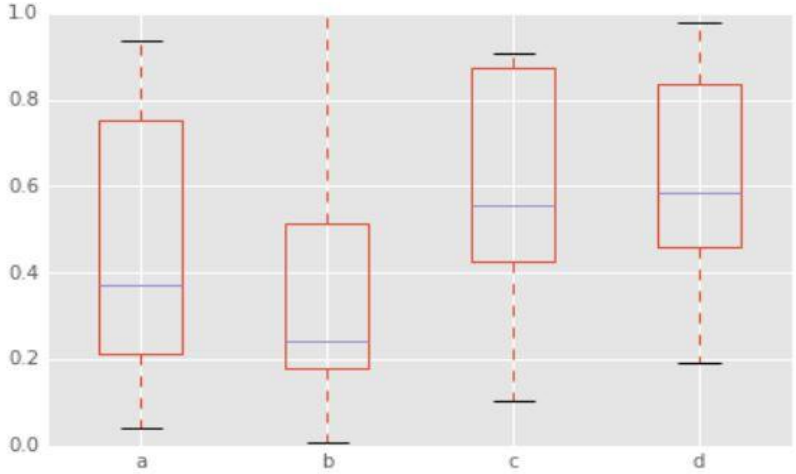
- **Use Case:** Summarizing data distribution and identifying outliers.
- **Method:** plot.box()

Example

```
df = pd.DataFrame({'A': [5, 7, 8, 5, 6], 'B': [10, 15, 8, 7, 9]})

df.plot(kind='box', title='Box Plot of Data')
```

Output:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1271fa198>
```



7. Area Plot

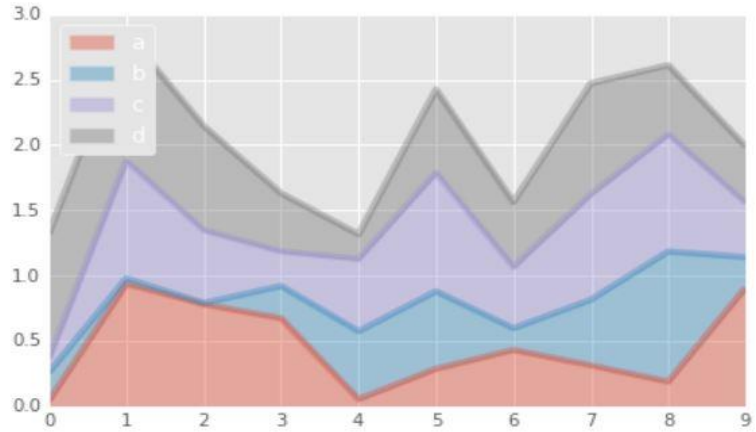
- **Use Case:** Visualizing the magnitude of values over time.
- **Method:** plot.area()

Example

```
df.plot.area(alpha=0.4)
```

Output:

```
<matplotlib.axes._subplots.AxesSubplot at 0x126222978>
```



8. Density Plot (KDE)

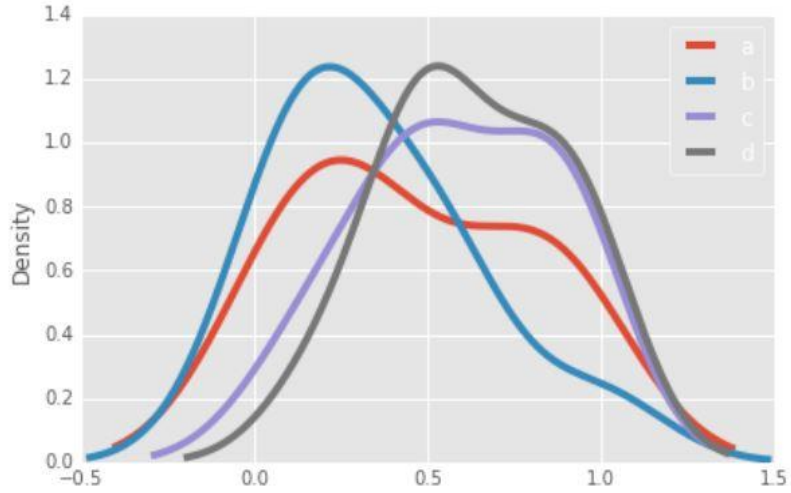
- **Use Case:** Showing the probability density of a continuous variable.
- **Method:** plot.kde()

Example

```
data = pd.Series([1, 2, 2, 3, 3, 4, 5, 6])
data.plot(kind='kde', title='Density Plot')
```

Output:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1276f7940>
```



9. Multiple Subplots

- **Use Case:** Displaying multiple graphs within a single figure.
- **Method:** subplots=True

Example

```
df = pd.DataFrame({'A': [1, 2, 3], 'B': [4, 5, 6]})
df.plot(subplots=True, layout=(1, 2),
figsize=(8, 4), title='Multiple Subplots')
```

10. Stacked Bar Plot

- **Use Case:** Comparing parts of multiple groups.
- **Method:** plot.bar(stacked=True)

Example

```
df = pd.DataFrame({'A': [3, 2, 5], 'B': [1, 4, 6]},
 index=['X', 'Y', 'Z'])
df.plot(kind='bar', stacked=True, title='Stacked Bar Plot')
```

11. Lag Plot

- **Use Case:** Visualizing the relationship between a time series and a lagged version of itself.
- **Method:** Uses Pandas along with Matplotlib.

Example

```
from pandas.plotting import lag_plot
data = pd.Series([1, 2, 3, 4, 3, 2, 1])
lag_plot(data) plt.title('Lag Plot')
plt.show()
```

Comparison: Matplotlib vs Pandas

Aspect	Matplotlib	Pandas
Purpose	A general-purpose plotting library for creating custom visualizations.	Primarily a data manipulation library with basic plotting capabilities.
Ease of Use	Requires more code and customization for plotting.	Easier to generate plots directly from Data Frames and Series.
Complexity	Suitable for complex, highly customized visualizations.	Best for quick, simple visualizations during data analysis.
Integration	Can integrate with Pandas, Seaborn, and other libraries for advanced features.	Uses Matplotlib as its backend for plotting functions.
Plot Types	Supports a wide range of plots (e.g., 3D plots, polar plots, animations).	Supports basic plots like line, bar, pie, scatter, and histogram.
Customization	Highly customizable (control over axes, labels, grids, etc.)	Limited customization options.
Performance	Requires more effort and code to optimize performance.	Faster for small to medium datasets but lacks scalability for large datasets.

INTERMEDIATE LEVEL

Air quality index (AQI) analysis

Conduct an in-depth analysis of the Air Quality Index (AQI) in Delhi, addressing the specific environmental challenges faced by the city. Define research questions centered around key pollutants, seasonal variations, and the impact of geographical factors on air quality. Utilize statistical analyses and visualizations to gain insights into the dynamics of AQI in Delhi, offering a comprehensive understanding that can inform targeted strategies for air quality improvement and public health initiatives in the region.

Introduction to the Air Quality Index Report: Delhi

Delhi, one of the most densely populated and industrialized cities in the world, faces significant challenges related to air pollution. The Air Quality Index (AQI) serves as a crucial tool for evaluating and communicating the state of air quality in the region. This report provides an in-depth analysis of the AQI in Delhi, derived from a dataset that includes key pollutants: carbon monoxide (CO), nitrogen oxides (NO and NO2), ozone (O3), sulfur dioxide (SO2), particulate matter (PM2.5 and PM10), and ammonia (NH3). The dataset encompasses air quality measurements collected from various monitoring stations across the city over the past year. These pollutants have diverse sources, including vehicular emissions, industrial discharges, construction activities, and seasonal factors like crop burning, all of which significantly influence air quality levels. In this report, we will analyze trends in pollutant concentrations and their correlation with AQI values, highlighting critical periods of poor air quality and their implications for public health. We will also discuss the potential health risks associated with different pollutant levels, particularly for vulnerable populations.

Air Quality Index Analysis: Process We Can Follow

Air Quality Index Analysis aims to provide a numerical value representative of overall air quality, essential for public health and environmental management. Below are the steps we can follow for the task of Air Quality Index Analysis:

1. Gather air quality data from various sources, such as government monitoring stations, sensors, or satellite imagery.
2. Clean and preprocess the collected data.
3. Calculate the Air Quality Index using standardized formulas and guidelines provided by environmental agencies.
4. Create visualizations, such as line charts or heatmaps, to represent the AQI over time or across geographical regions.
5. Compare the AQI metrics of the location with the recommended air quality metrics.

Air Quality Index Analysis using Python

Now, let's get started with the task of Air Quality Index Analysis by importing the necessary Python libraries and the dataset:

```
import pandas as pd
import numpy as np
from google.colab import files
uploaded=files.upload()

data = pd.read_csv("delhiaqi.csv")
print(data.head())
```

	date	co	no	no2	o3	so2	pm2_5	pm10	nh3
0	2023-01-01 00:00:00	1655.58	1.66	39.41	5.90	17.88	169.29	194.64	5.83
1	2023-01-01 01:00:00	1869.20	6.82	42.16	1.99	22.17	182.84	211.08	7.66
2	2023-01-01 02:00:00	2510.07	27.72	43.87	0.02	30.04	22.25	260.68	11.40
3	2023-01-01 03:00:00	3150.94	55.43	44.55	0.85	35.76	252.90	304.12	13.55
4	2023-01-01 04:00:00	3471.37	68.84	45.24	5.45	39.10	266.36	322.80	14.19

The date column in the dataset into a datetime data type and move forward:

```
data['date'] = pd.to_datetime(data['date'])
```

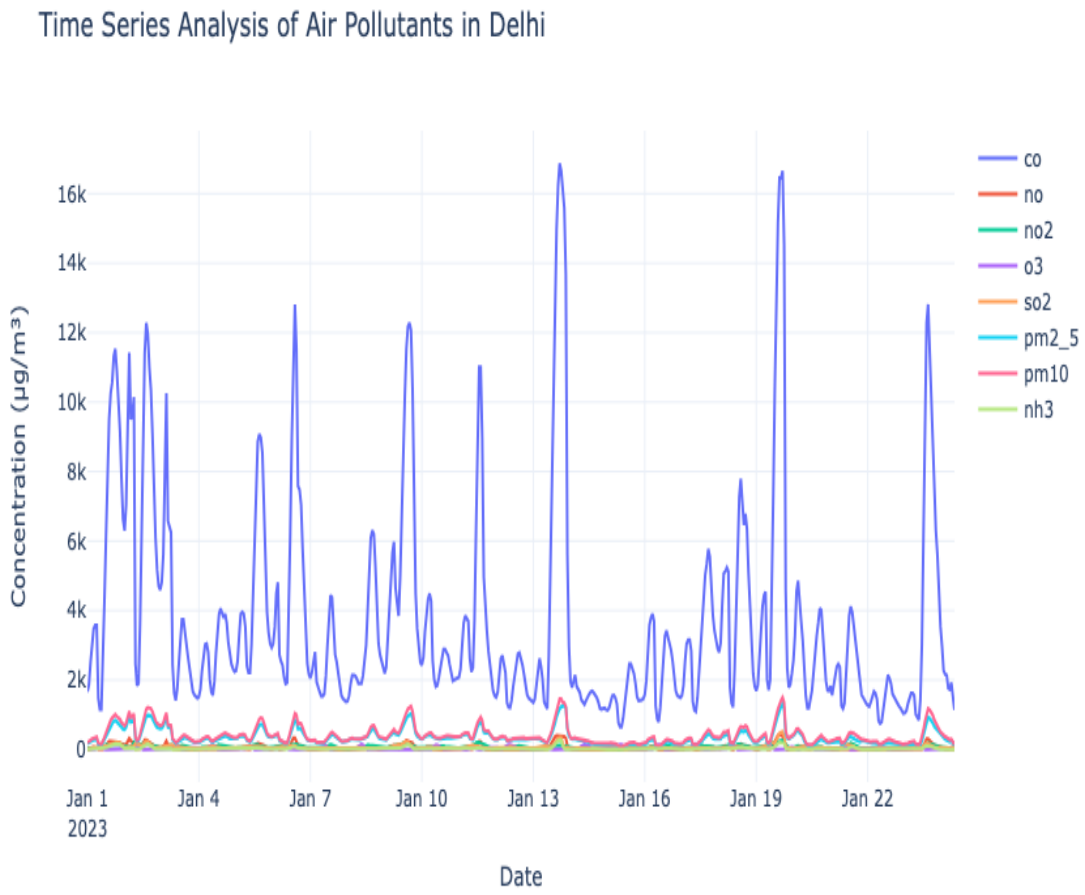
Now, let's have a look at the descriptive statistics of the data:

```
print(data.describe())
```

	co	no	no2	o3	so2	pm2_5	pm10	nh3
count	561.000000	561.000000	561.000000	561.000000	561.000000	561.000000	561.000000	561.000000
mean	3814.942210	51.181979	75.292496	30.141943	64.655936	358.256364	420.988414	26.425062
std	3227.744681	83.904476	42.473791	39.979405	61.073080	227.359117	271.287026	36.563094
min	654.220000	0.000000	13.370000	0.000000	5.250000	60.100000	69.080000	0.630000
25%	1708.980000	3.380000	44.550000	0.070000	28.130000	204.450000	240.900000	8.230000
50%	2590.180000	13.300000	63.750000	11.800000	47.210000	301.170000	340.900000	14.820000
75%	4432.680000	59.010000	97.330000	47.210000	77.250000	416.650000	482.570000	26.350000
max	16876.220000	425.580000	263.210000	164.510000	511.170000	1310.200000	1499.270000	267.510000

Now let’s have a look at the intensity of each pollutant over time in the air quality:

```
# time series plot for each air pollutant

fig = go.Figure()
for pollutant in ['co', 'no', 'no2', 'o3', 'so2', 'pm2_5', 'pm10', 'nh3']:
fig.add_trace(go.Scatter(x=data['date'], y=data[pollutant], mode='lines',
name=pollutant))
fig.update_layout(title='Time Series Analysis of Air Pollutants in Delhi',
xaxis_title='Date', yaxis_title='Concentration (µg/m³)')
fig.show()
```



In the above code, we are creating a time series plot for each air pollutant in the dataset. It helps analyze the intensity of air pollutants over time.

Calculating Air Quality Index

Now, before moving forward, we need to calculate the air quality index and its category. AQI is typically computed based on the concentration of various pollutants, and each pollutant has its sub-index.

Here's how we can calculate AQI:

```
# Define AQI breakpoints and corresponding AQI values
aqi_breakpoints = [
    (0, 12.0, 50), (12.1, 35.4, 100), (35.5, 55.4, 150),
    (55.5, 150.4, 200), (150.5, 250.4, 300), (250.5, 350.4, 400),
    (350.5, 500.4, 500)]

def calculate_aqi(pollutant_name, concentration):
 for low, high, aqi in aqi_breakpoints:
 if low <= concentration <= high:
 return aqi
 return None
 def calculate_overall_aqi(row):
 aqi_values = []
 pollutants = ['co', 'no', 'no2', 'o3', 'so2', 'pm2_5', 'pm10', 'nh3']
 for pollutant in pollutants:
 aqi = calculate_aqi(pollutant, row[pollutant])
        if aqi is not None:
            aqi_values.append(aqi)
    return max(aqi_values)
# Calculate AQI for each row
data['AQI'] = data.apply(calculate_overall_aqi, axis=1)
# Define AQI categories
aqi_categories = [
    (0, 50, 'Good'), (51, 100, 'Moderate'), (101, 150, 'Unhealthy for Sensitive Groups'),
    (151, 200, 'Unhealthy'), (201, 300, 'Very Unhealthy'), (301, 500, 'Hazardous')]
def categorize_aqi(aqi_value):
    for low, high, category in aqi_categories:
        if low <= aqi_value <= high:
            return category
    return None

# Categorize AQI
data['AQI Category'] = data['AQI'].apply(categorize_aqi)
print(data.head())
```

```
       date                    co          no          no2    o3       so2        pm10                          \
0 2023-01-01 00:00:00    1655.58        1.66  39.41    5.90   17.88    169.29
1 2023-01-01 01:00:00    1869.20        6.82  42.16   1.99    22.17    182.84
2 2023-01-01 02:00:00    2.07  276      43.87  0.02   30.04   220.25   260.68
3 2023-01-01 03:00:00    3.94  55.43    44.55  0.85   35.76   252.90   304.12
4 2023-01-01 04:00:00    34.37  68.84   45.24  5.45   39.10   266.36   322.80

    nh3  AQI    AQI Category
0   5.83  300  Very Unhealthy
1   7.66  300  Very Unhealthy
2  11.40  400      Hazardous
3  13.55  400      Hazardous
4  14.19  400      Hazardous
```

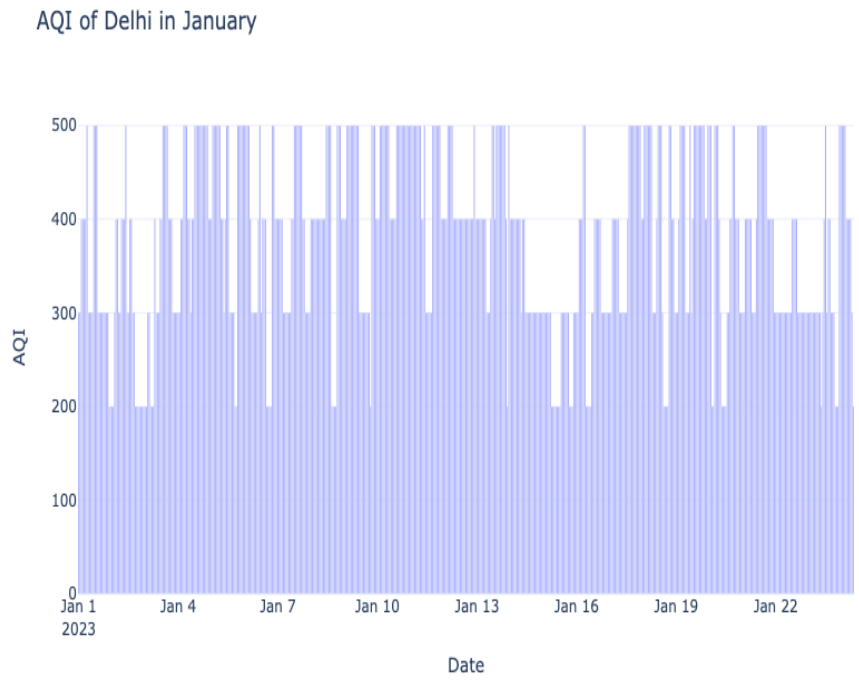
In the above code, we are defining AQI breakpoints and corresponding AQI values for various air pollutants according to the Air Quality Index (AQI) standards. The aqi_breakpoints list defines the concentration ranges and their corresponding AQI values for different pollutants.

We then define two functions:
1.calculate_aqi: to calculate the AQI for a specific pollutant and concentration by finding the appropriate range in the aqi_breakpoints
2.calculate_overall_aqi: to calculate the overall AQI for a row in the dataset by considering the maximum AQI value among all pollutants

The calculated AQI values are added as a new column in the dataset. Additionally, we defined AQI categories in the aqi_categories list and used the categorize_aqi function to assign an AQI category to each AQI value. The resulting AQI categories are added as a new column as AQI Category in the dataset.

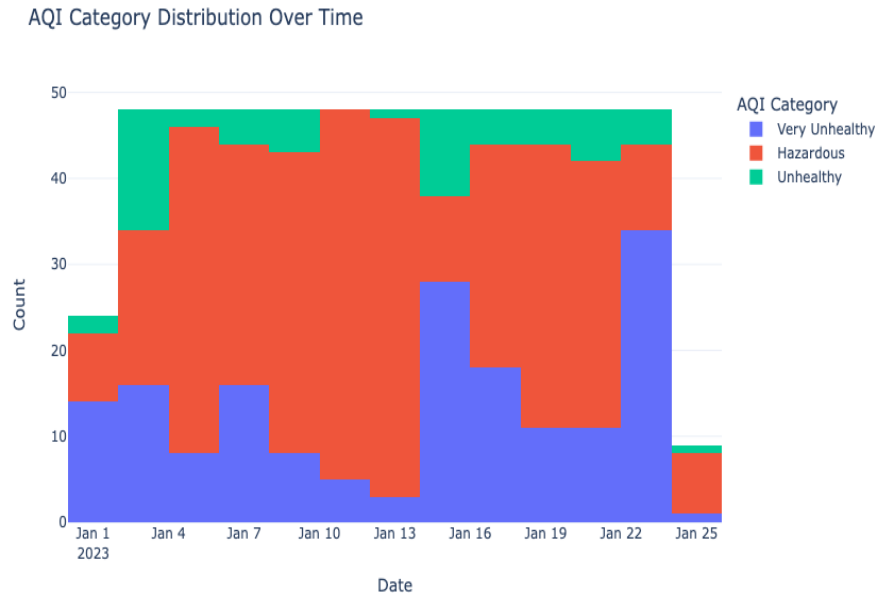
Analyzing AQI of Delhi
Now, let’s have a look at the AQI of Delhi in January:

```
# AQI over time
fig = px.bar(data, x="date", y="AQI",
             title="AQI of Delhi in January")
fig.update_xaxes(title="Date")
fig.update_yaxes(title="AQI")
fig.show()
```



Now, let's have a look at the AQI category distribution:

```
fig = px.histogram(data, x="date",
                   color="AQI Category",
                   title="AQI Category Distribution Over Time")
fig.update_xaxes(title="Date")
fig.update_yaxes(title="Count")
fig.show()
```



Now, let's have a look at the distribution of pollutants in the air quality of Delhi:

```
# Define pollutants and their colors
pollutants = ["co", "no", "no2", "o3", "so2", "pm2_5", "pm10", "nh3"]
pollutant_colors = px.colors.qualitative.Plotly
# Calculate the sum of pollutant concentrations
total_concentrations = data[pollutants].sum()
# Create a DataFrame for the concentrations
concentration_data = pd.DataFrame({
    "Pollutant": pollutants,
    "Concentration": total_concentrations
})
# Create a donut plot for pollutant concentrations
fig = px.pie(concentration_data, names="Pollutant", values="Concentration",
             title="Pollutant Concentrations in Delhi",
             hole=0.4, color_discrete_sequence=pollutant_colors)
# Update layout for the donut plot
fig.update_traces(textinfo="percent+label")
fig.update_layout(legend_title="Pollutant")
# Show the donut plot
fig.show()
```