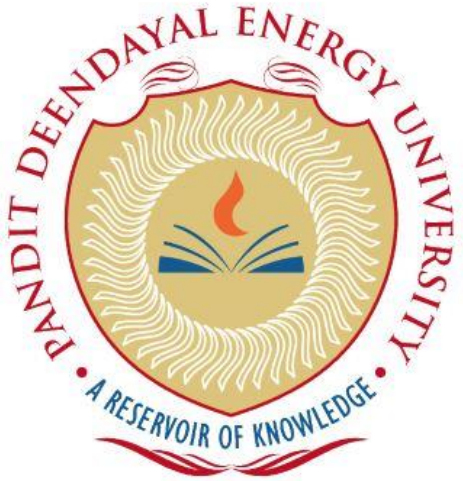
PANDIT DEENDAYAL ENERGY UNIVERSITY

SCHOOL OF TECHNOLOGY



Machine Learning Lab

20CP401P

LAB MANUAL

B.Tech. (Computer Science and Engineering)

Semester 7

Submitted To:

Dr. Archana Nigam

Submitted By:

HARSH SHAH

21BCP359

G11 Batch

INDEX

LAB ASSIGNMENT 1

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Discuss and analyze different data visualization tools.		

Objective

The objective of this lab assignment is to explore and analyse various data visualization tools used for representing and understanding complex datasets. Through this assignment, you will gain insights into the strengths, weaknesses, and practical applications of different visualization tools.

Dataset Used: U.S. International Air Traffic data (1990-2020) - Kaggle

Introduction to Data Visualization

Data visualization is the graphical representation of information and data. By using visual elements like charts, graphs, and maps, data visualization tools provide an accessible way to see and understand trends, outliers, and patterns in data. It's an essential skill in the data analysis process, helping to make complex data more understandable, insightful, and actionable.

Key Types of Data Visualizations:

- **Charts**: Including bar charts, line charts, pie charts, and histograms, these are used to compare different categories or show changes over time.
- **Graphs**: Such as scatter plots and area graphs, these help in understanding relationships between variables.
- **Maps**: Geographic data can be visualized using maps to highlight spatial patterns and distributions.
- **Infographics**: These combine various visualization elements to tell a story or provide a comprehensive overview of data.
- **Dashboards**: Interactive platforms that allow users to manipulate data and visuals to explore different perspectives and insights.

Data Visualisation Tools

- **Microsoft Excel**: A widely used tool that offers basic to advanced charting and graphing capabilities.
- **Python Libraries**: Libraries like Matplotlib, Seaborn, and Plotly are popular among data scientists for creating a wide range of static, animated, and interactive visualizations.
- **Tableau**: A powerful tool for creating interactive and shareable dashboards.
- **Power BI**: A business analytics service by Microsoft that provides interactive visualizations and business intelligence capabilities.
- **Google Data Studio**: A free tool that transforms your data into informative, easy-to-read, and shareable dashboards and reports.
- **R/JS Libraries**: Libraries like ggplot2(R), plotly(R), D3.js(JS), plotly(JS) are popular among for creating a wide range of static, animated, and interactive visualizations.

Brief Overview of Tool Capabilities and Features

a) Matplotlib (Python)

- Matplotlib is a versatile plotting library in Python that produces publication-quality figures in a variety of formats and interactive environments.
- Wide Range of Plots: Supports line plots, scatter plots, bar charts, histograms, pie charts, error bars, and more.
- Subplots and Axes: Allows creation of complex, multi-plot layouts.
- Use Cases: Scientific Research, Financial Analysis

b) Seaborn (Python)

- Seaborn is a statistical data visualization library based on Matplotlib, providing a high-level interface for drawing attractive and informative statistical graphics.
- Complex Plots Simplified: Simplifies the creation of complex visualizations such as heatmaps, time series, violin plots, and pair plots.
- Statistical Plotting: Integrates with pandas Data Frames and supports statistical aggregation and plotting.
- Use Cases: Exploratory Data Analysis (EDA), Statistical Data Visualization

c) Power BI

- Power BI is a business analytics service by Microsoft that delivers insights to enable fast, informed decisions.
- Interactive Dashboards: Allows creation of interactive and shareable dashboards.
- Data Connectivity: Connects to a wide variety of data sources, including databases, web services, and Excel spreadsheets.
- Data Modelling: Offers robust data modelling and transformation capabilities.
- Real-Time Analytics: Supports real-time data visualization and streaming analytics.
- Use Cases: Business Intelligence and Reporting, Real-Time Data Monitoring

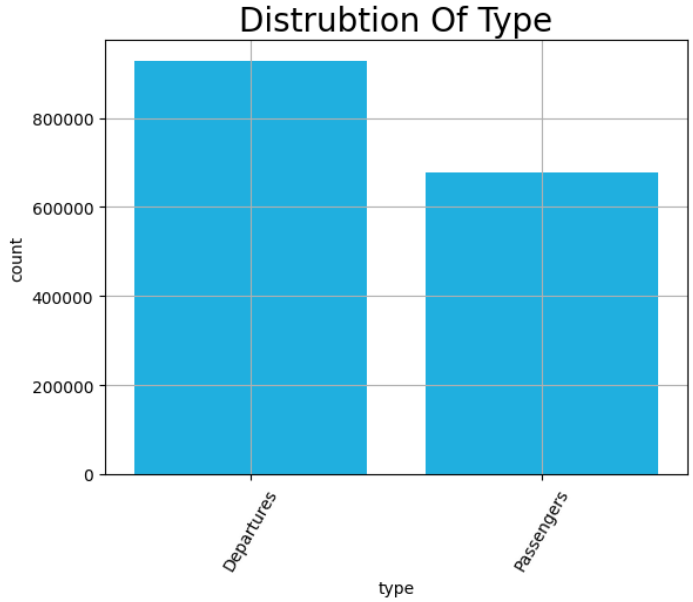
d) Plotly (Python)

- Plotly is an interactive graphing library for Python, known for its high-quality and interactive plots.
- Interactive Graphs: Produces interactive plots that can be embedded in web applications or dashboards.
- Dash by Plotly: Integrated with Dash, a framework for building interactive web applications with Python.
- Ease of Use: User-friendly API and integration with pandas for quick and easy plotting.
- Cross-Platform: Plots can be viewed in Jupyter Notebooks, standalone HTML files, or web applications.
- Use Cases: Interactive Web Applications, 3D Data Visualization

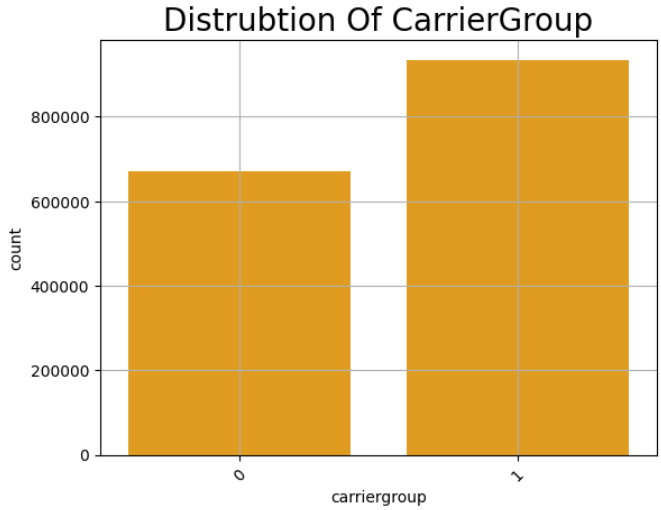
Code Snippets

1. Using Seaborn and Matplotlib

```
sns.countplot(x='type',data=full_data, color="deepskyblue")
plt.title('Distrubtion Of Type',fontsize=20 , color="black")
plt.grid(True)
plt.xticks(rotation=60)
plt.show()
```

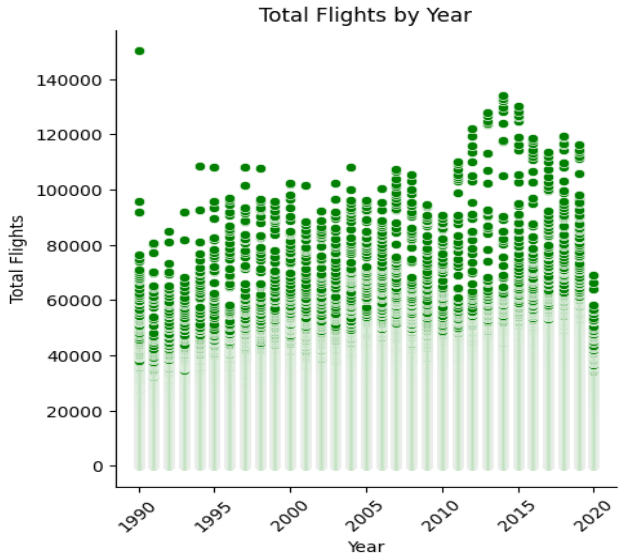



```
sns.countplot(x='carriergroup',data=full_data, color="orange")
plt.title('Distrubtion Of CarrierGroup',fontsize=20)
plt.grid(True)
plt.xticks(rotation=45)
plt.show()
```

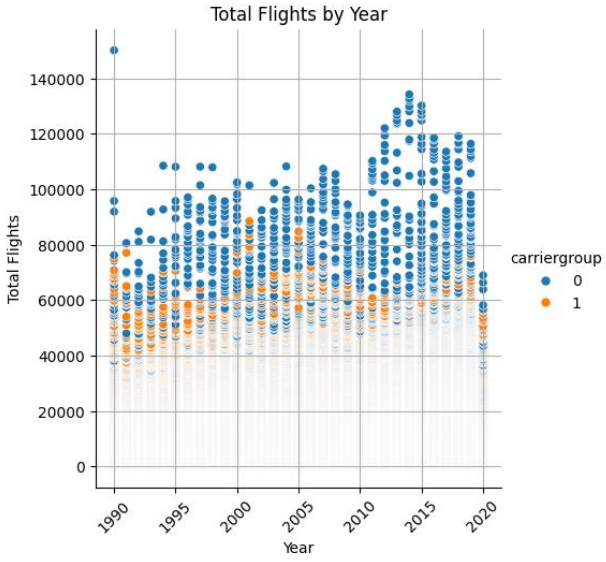



```
plt.figure(figsize=(10, 6))
sns.relplot(x='Year', y='Total', data=full_data ,  color='deepskyblue')
```

```
plt.xlabel('Year')
plt.ylabel('Total Flights')
plt.title('Total Flights by Year')
plt.xticks(rotation=45)
plt.show()
```

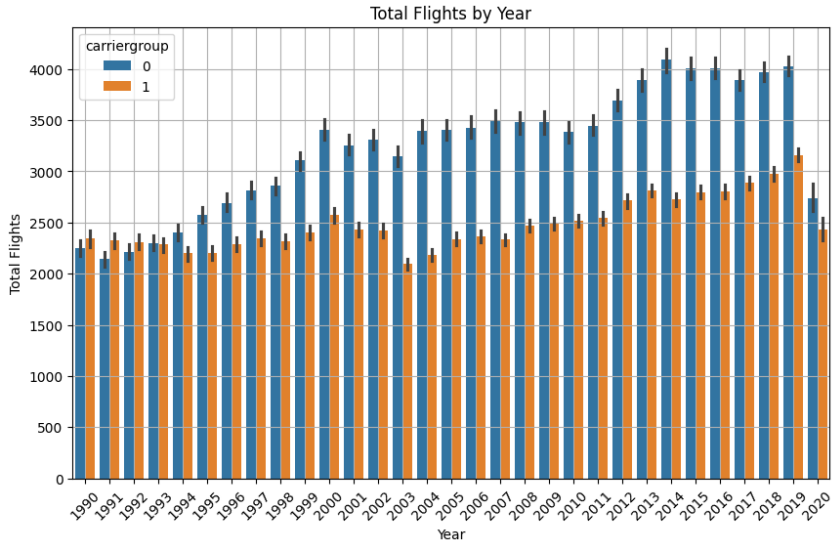



```
plt.figure(figsize=(10, 6))
sns.relplot(x='Year', y='Total',hue='carriergroup',data=full_data, color='green')
plt.xlabel('Year')
plt.ylabel('Total Flights')
plt.title('Total Flights by Year')
plt.grid(True)
plt.xticks(rotation=45)
plt.show()
```

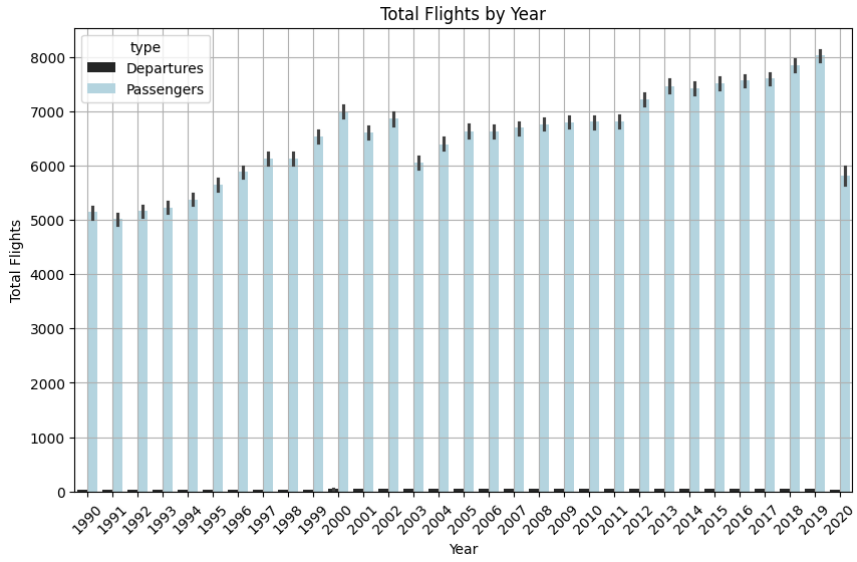



```
plt.figure(figsize=(10, 6))
sns.barplot(x='Year', y='Total',hue='carriergroup',data=full_data)
plt.xlabel('Year')
```

```
plt.ylabel('Total Flights')
plt.title('Total Flights by Year')
plt.grid(True)
plt.xticks(rotation=45)
plt.show()
```

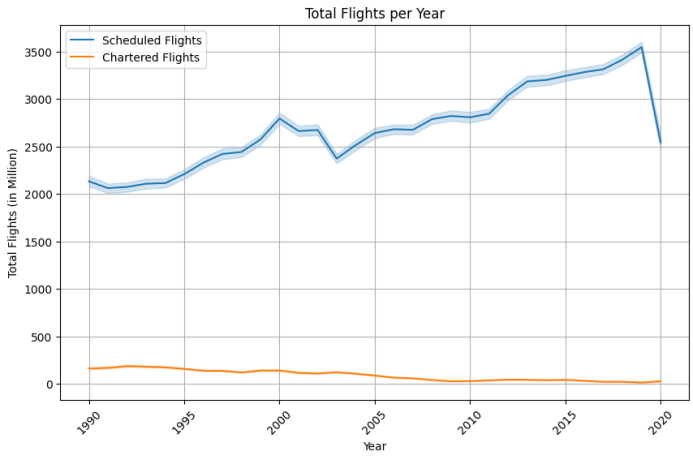



```
plt.figure(figsize=(10, 6))
sns.barplot(x='Year', y='Total',hue='type',data=full_data, color='lightblue' )
plt.xlabel('Year')
plt.ylabel('Total Flights')
plt.title('Total Flights by Year')
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```

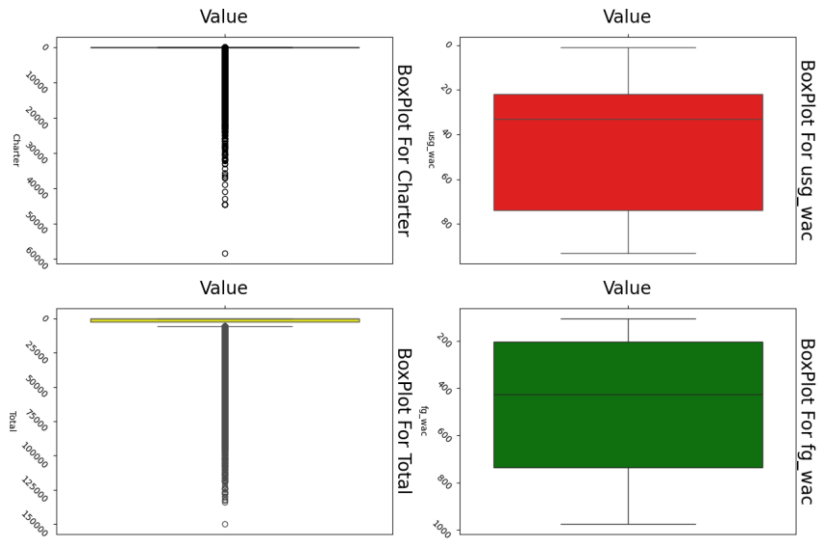



```
plt.figure(figsize=(10, 6))
sns.lineplot(x='Year', y='Scheduled', data=full_data, label='Scheduled Flights')
sns.lineplot(x='Year', y='Charter', data=full_data, label='Chartered Flights')
```

```
sns.color_palette("flare", as_cmap=True)
plt.title('Total Flights per Year')
plt.xlabel('Year')
plt.ylabel('Total Flights (in Million)')
plt.xticks(rotation=45)
plt.grid(True)
plt.legend()
plt.show()
```

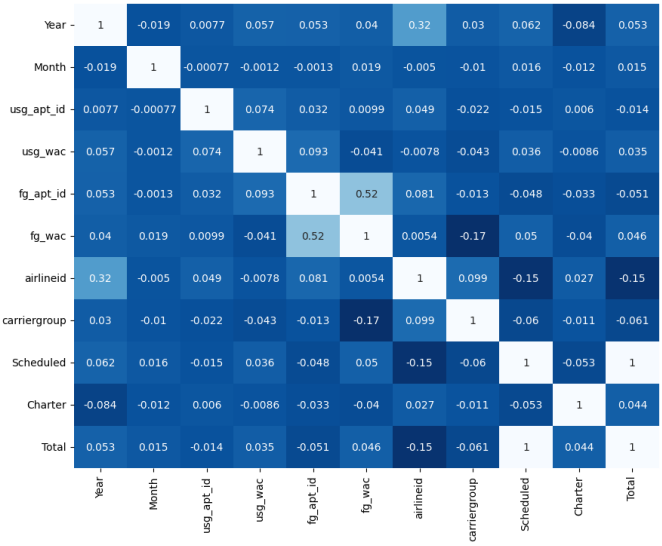



```
plt.figure(figsize=(10,15))
x=1
for i,j in zip(['usg_wac','fg_wac','Charter','Total'],['red','green','black','yellow']):
  plt.subplot(2,2,x)
  sns.boxplot(x=i,data=full_data,color=j)
  plt.ylabel('Value',fontsize=20)
  plt.title(f'BoxPlot For {i}',fontsize=20)
  plt.xticks(rotation=45)
  x+=1
```

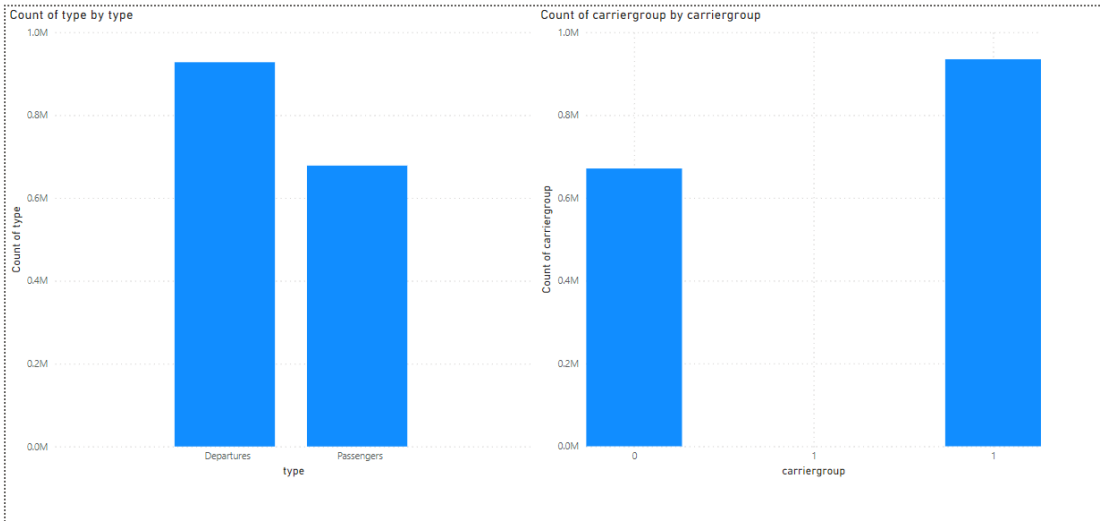


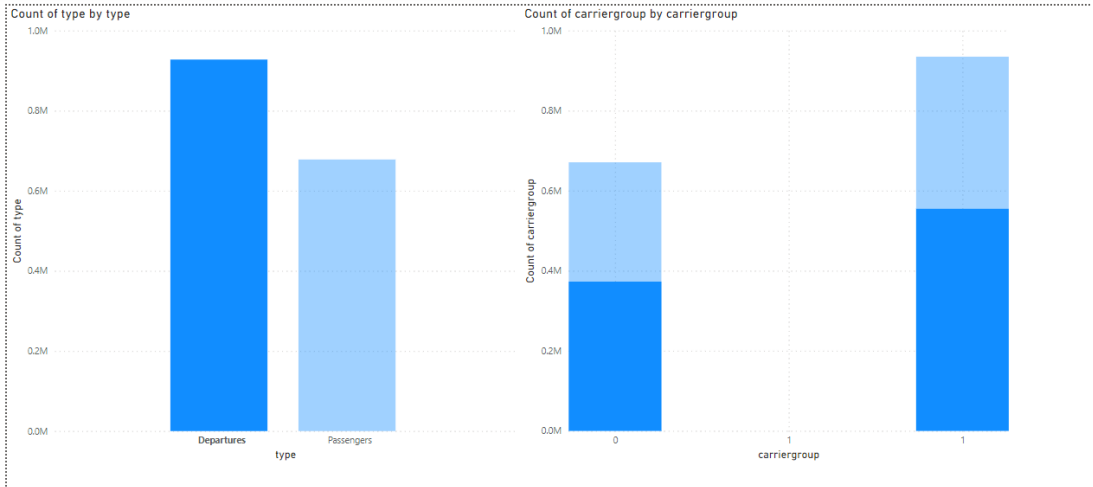

```
numerical_data = full_data.select_dtypes(include=['number'])
correlation_matrix = numerical_data.corr()
plt.figure(figsize=(10, 8))
```

sns.heatmap(correlation_matrix, *cmap*='Blues_r', *annot*=True, *cbar*=False)

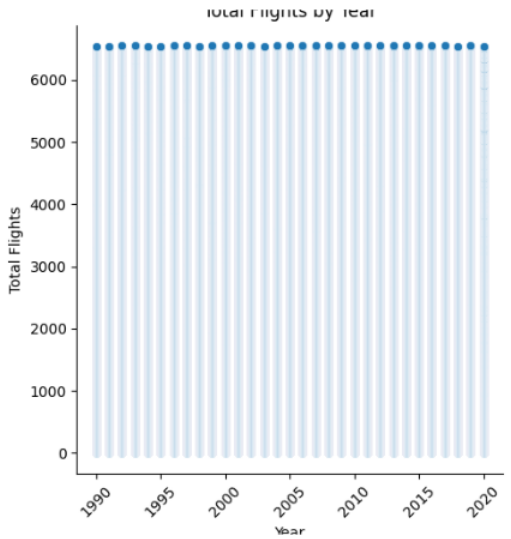


2. Using POWERBI

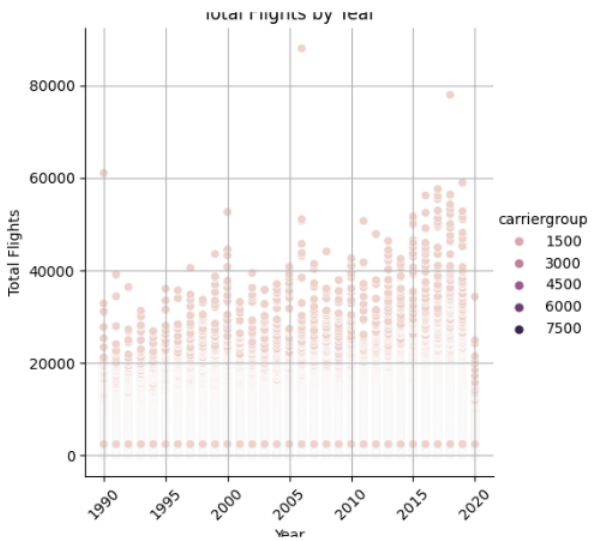




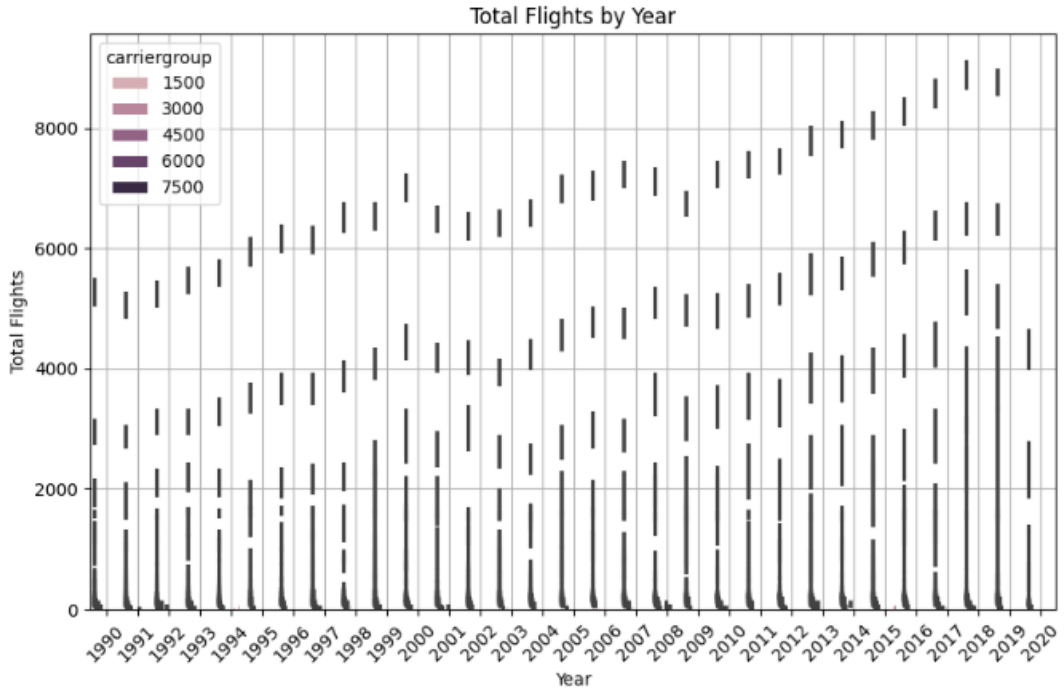
Total and Year



Count of carriergroup, Year and Total

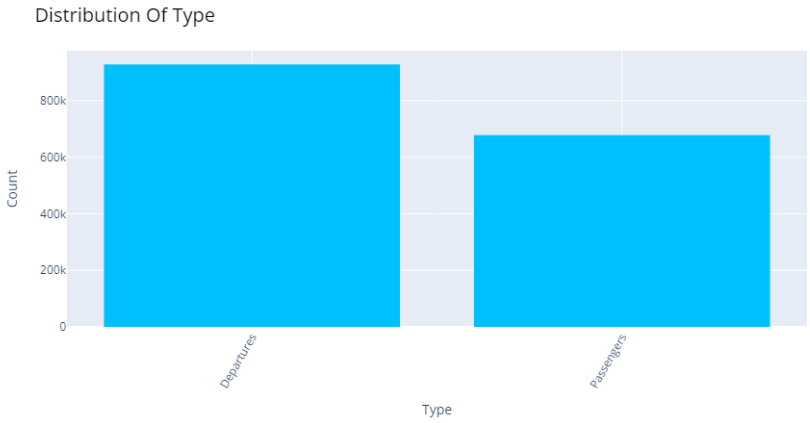


Count of carriergroup, Total and Year

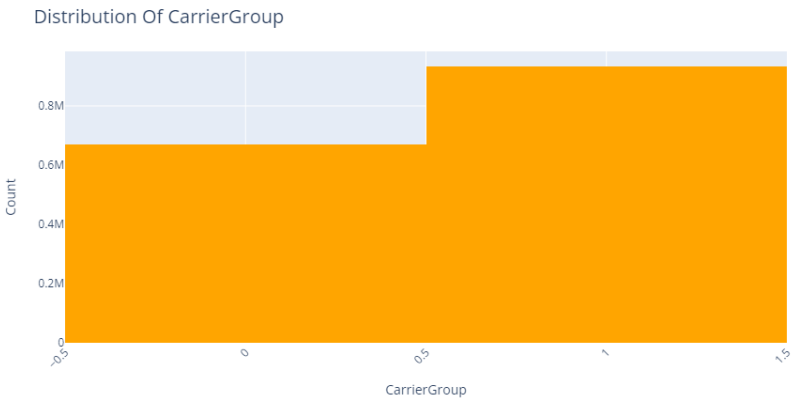


3. Using Plotly (Python)

```
fig = px.histogram(full_data, x='type', color_discrete_sequence=['deepskyblue'])
fig.update_layout(
    title='Distribution Of Type',
    title_font_size=20,
    title_font_color='black',
    xaxis_title='Type',
    yaxis_title='Count',
    xaxis_tickangle=-60,
    xaxis_showgrid=True,
    yaxis_showgrid=True
)
fig.show()
```

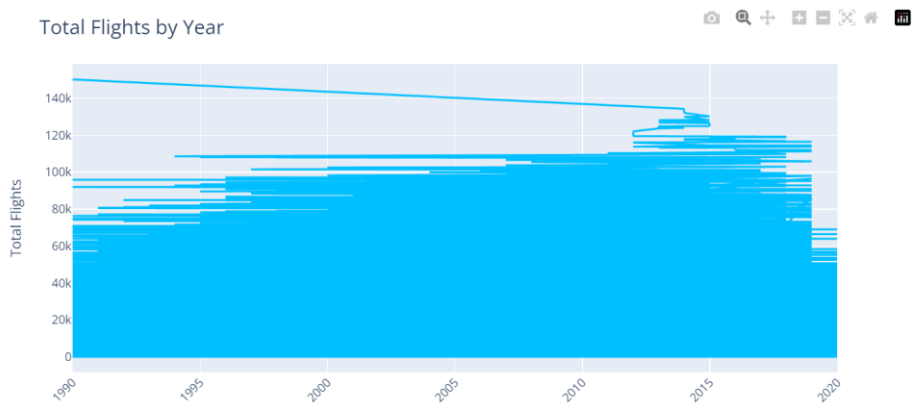



```
fig = px.histogram(full_data, x='carriergroup', color_discrete_sequence=['orange'])
fig.update_layout(
    title='Distribution Of CarrierGroup',
    title_font_size=20,
    xaxis_title='CarrierGroup',
    yaxis_title='Count',
    xaxis_tickangle=-45,
    xaxis_showgrid=True,
    yaxis_showgrid=True
)
fig.show()
```

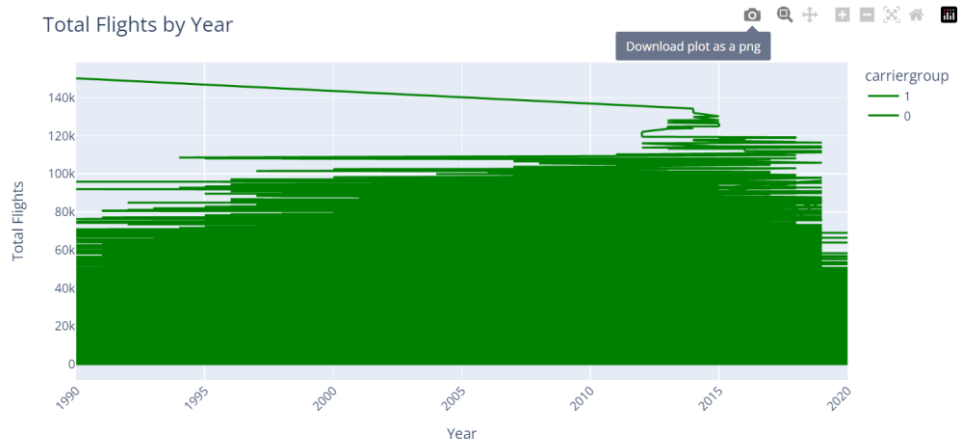



```
fig = px.line(full_data, x='Year', y='Total', line_shape='linear', color_discrete_sequence=['deepskyblue'])
```

```
fig.update_layout(
    title='Total Flights by Year',
    title_font_size=20,
    xaxis_title='Year',
    yaxis_title='Total Flights',
    xaxis_tickangle=-45
)
fig.show()
```

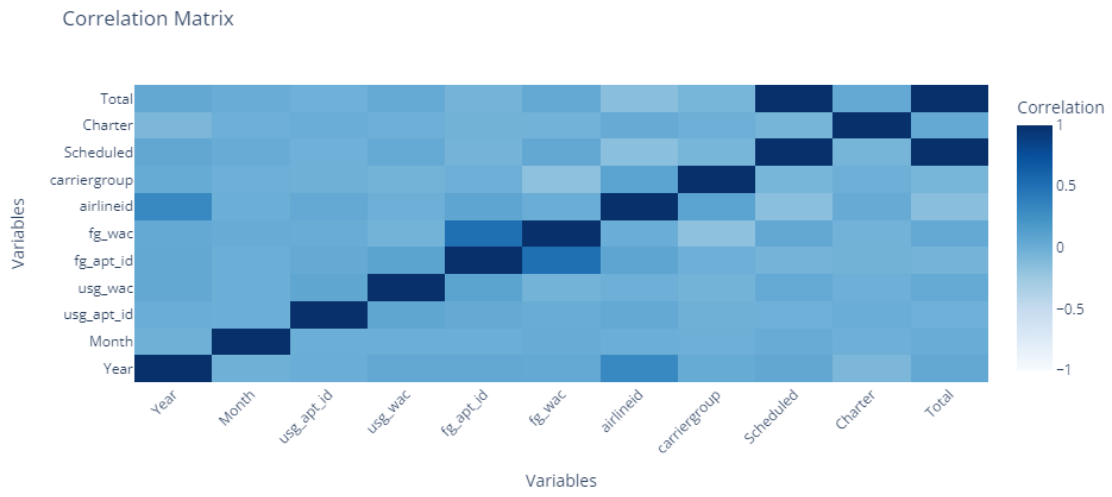



```
fig = px.line(full_data, x='Year', y='Total', color='carriergroup', line_shape='linear',
color_discrete_sequence=['green'])
fig.update_layout(
    title='Total Flights by Year',
    title_font_size=20,
    xaxis_title='Year',
    yaxis_title='Total Flights',
    xaxis_tickangle=-45,
    xaxis_showgrid=True,
    yaxis_showgrid=True
)
fig.show()
```




```
# Compute the correlation matrix
numerical_data = full_data.select_dtypes(include=['number'])
```

```
correlation_matrix = numerical_data.corr()

# Create the heatmap
fig = go.Figure(data=go.Heatmap(
    z=correlation_matrix.values,
    x=correlation_matrix.columns,
    y=correlation_matrix.columns,
    colorscale='Blues',
    colorbar_title='Correlation',
    zmid=0
))

# Update layout
fig.update_layout(
    title='Correlation Matrix',
    xaxis_title='Variables',
    yaxis_title='Variables',
    xaxis_nticks=len(correlation_matrix.columns),
    yaxis_nticks=len(correlation_matrix.columns),
    xaxis_tickangle=-45
)

fig.show()
```



LAB ASSIGNMENT 2

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Measurements of electric power consumption in one household with a one-minute sampling rate over a period of almost 4 years. Different electrical quantities and some sub-metering values are available.		

Objective

The objective of this lab assignment is to explore and analyse a dataset containing measurements of electric power consumption in a household over a period of almost 4 years. You will perform various data visualization tasks to gain insights into electrical quantities, sub-metering values, and overall trends.

Dataset: https://archive.ics.uci.edu/dataset/235/individual+household+electric+power+consumption

Task – 1: Load the data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
df = pd.read_csv( ./data/household_power_consumption.txt', sep=';',  _values=['nan', '?'] )
df.index = pd.to_datetime(df['Date'] +' '+ df['Time'], dayfirst=True)
df.index.name = 'dt'
df = df.drop(columns = ['Date', 'Time'])
```

 # Data Cleaning

```
df.isna().sum()
```

```
Global_active_power      25979
Global_reactive_power    25979
Voltage                  25979
Global_intensity         25979
Sub_metering_1           25979
Sub_metering_2           25979
Sub_metering_3           25979
dtype: int64
```

```
df.dropna(inplace=True)
df.isna().sum()
```

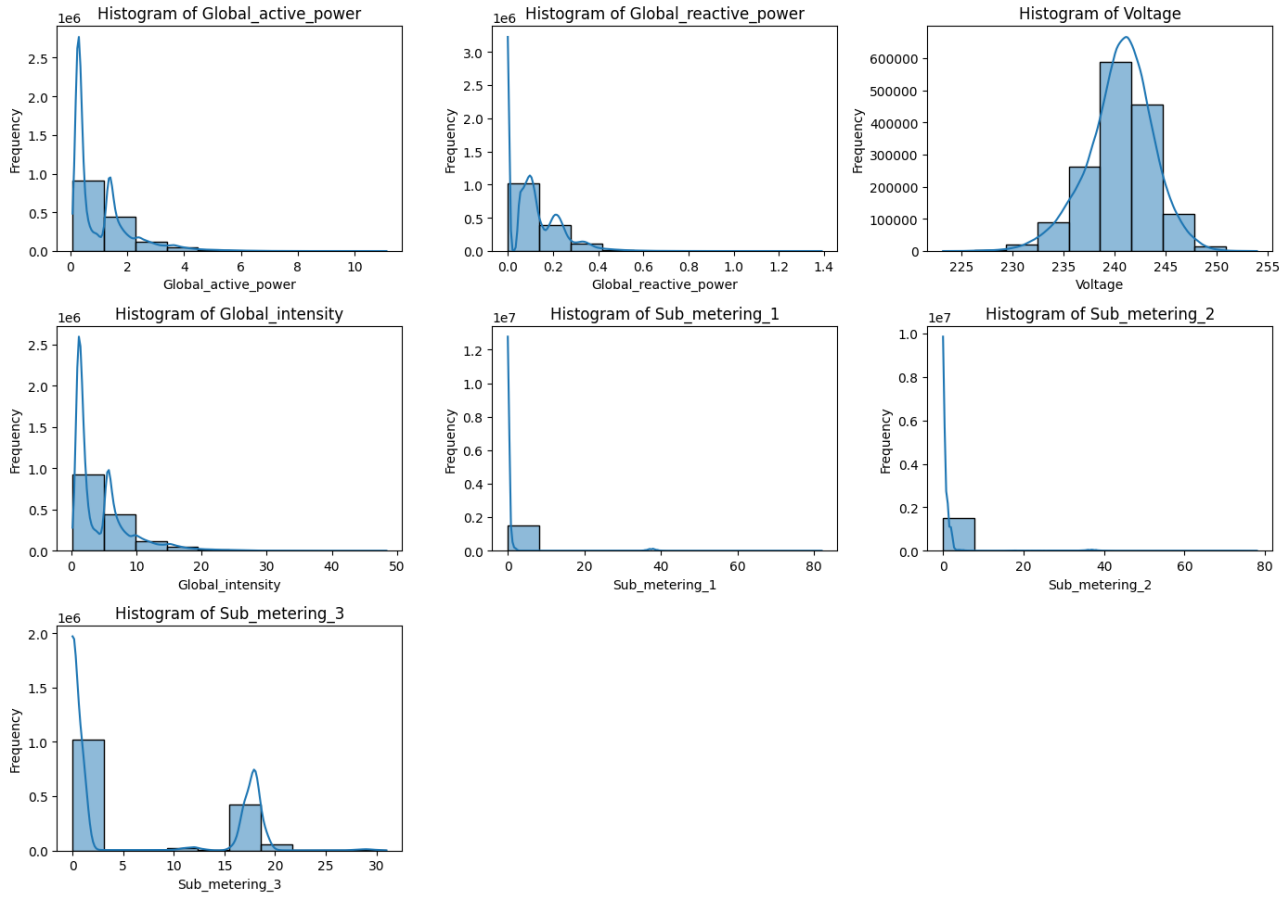
```
Global_active_power      0
Global_reactive_power    0
Voltage                  0
Global_intensity         0
Sub_metering_1           0
Sub_metering_2           0
Sub_metering_3           0
dtype: int64
```

Task – 2: Subset the data from the given dates (December 2006 and November 2009)

```
start_date = pd.Timestamp('2006-12-01')
end_date = pd.Timestamp('2009-11-30')
newdf = df.loc[start_date:end_date]
```

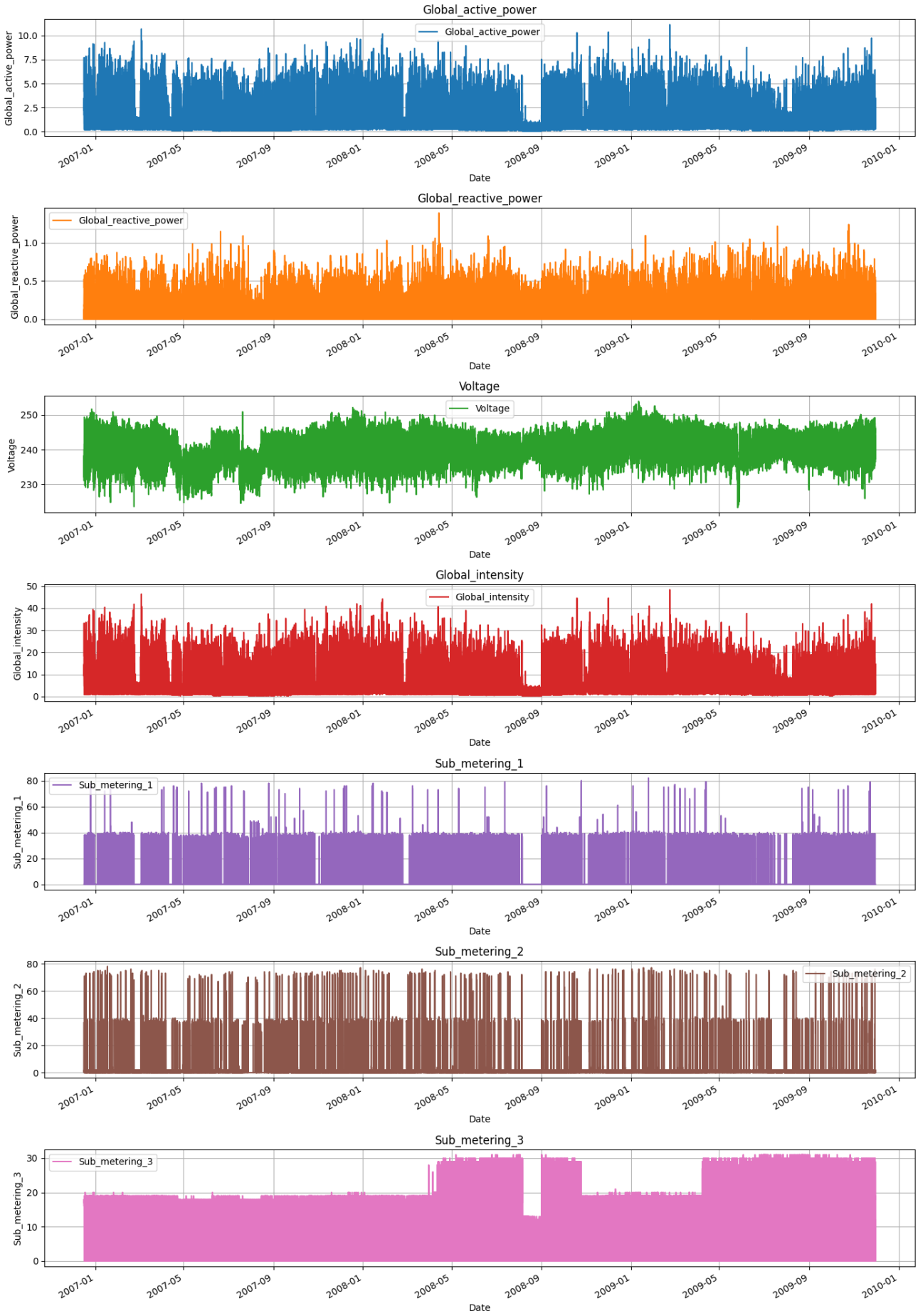
Task – 3: Create a histogram

```
plt.figure(figsize=(14, 10))
for i, column in enumerate(newdf.columns, 1):
    plt.subplot(3, 3, i)
    sns.histplot(newdf[column], kde=True, bins=10)
    plt.title(f'Histogram of {column}')
    plt.xlabel(column)
    plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



Task – 4: Create a Time series

```
plt.figure(figsize=(14, 20))
for i, column in enumerate(newdf.columns, 1):
    plt.subplot(7, 1, i)
    newdf[column].plot(title=column, xlabel='Date', ylabel=column, legend=True)
    plt.grid(True)
plt.tight_layout()
plt.show()
```


Global_active_power
Global_active_power
Global_active_power
Date
Global_reactive_power
Global_reactive_power
Global_reactive_power
Date
Voltage
Voltage
Voltage
Date
Global_intensity
Global_intensity
Global_intensity
Date
Sub_metering_1
Sub_metering_1
Sub_metering_1
Date
Sub_metering_2
Sub_metering_2
Sub_metering_2
Date
Sub_metering_3
Sub_metering_3
Sub_metering_3
Date

Task – 5: Create a plot for sub metering

df_melted = newdf.reset_index().melt(*id_vars*='dt', *value_vars*=['Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3'])

plt.figure(*figsize*=(12, 6))

sns.lineplot(*data*=df_melted, *x*='dt', *y*='value', *hue*='variable')

plt.title('Sub Metering Time Series')

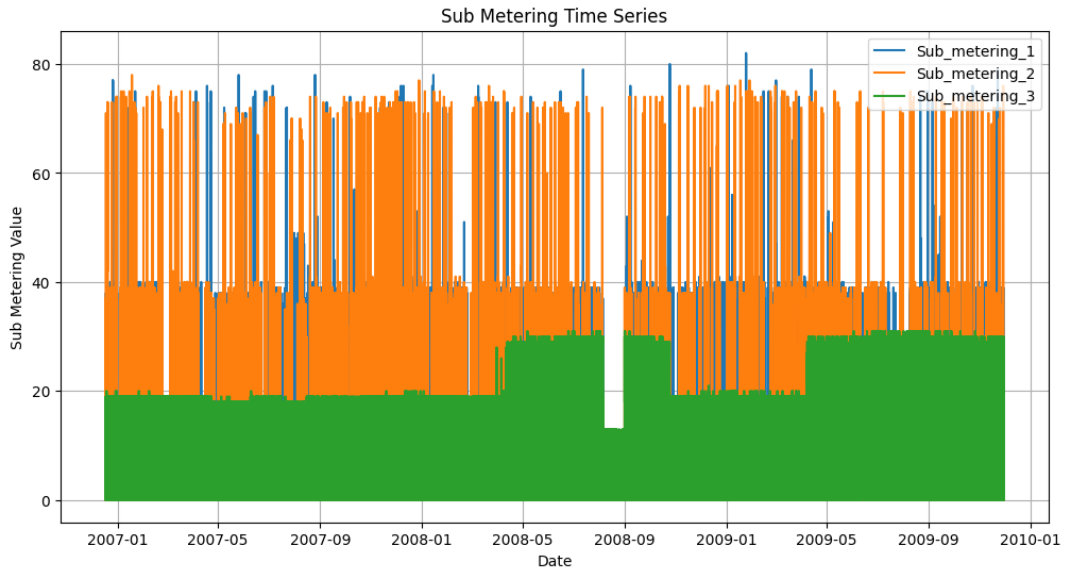
plt.xlabel('Date')

plt.ylabel('Sub Metering Value')

plt.legend(*loc*='upper right')

plt.grid(True)

plt.show()

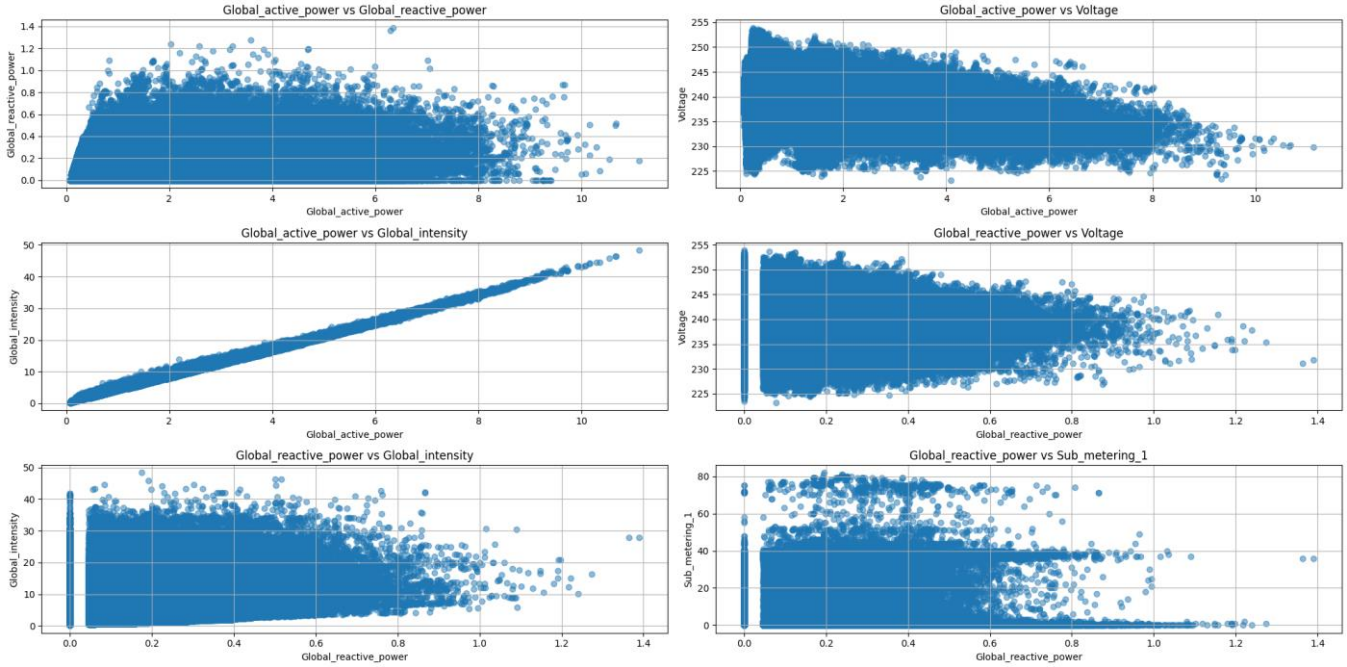


Task – 6: Create multiple other plots.

Scatter Plot

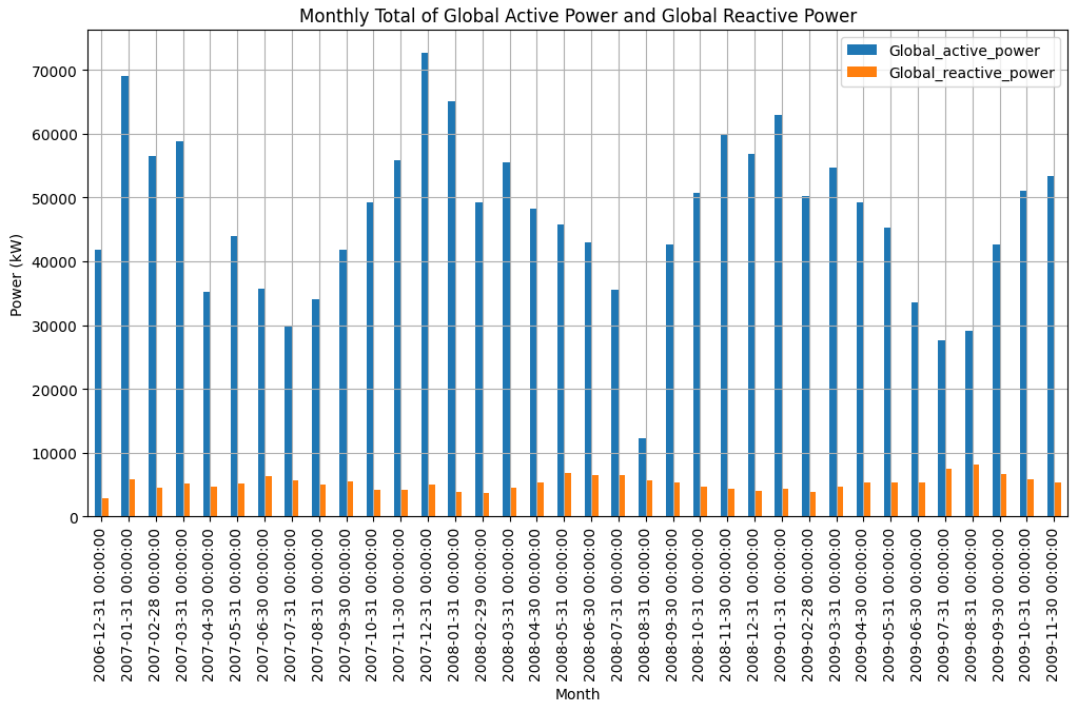
```
pairs = [
    ('Global_active_power', 'Global_reactive_power'),
    ('Global_active_power', 'Voltage'),
    ('Global_active_power', 'Global_intensity'),
    ('Global_reactive_power', 'Voltage'),
    ('Global_reactive_power', 'Global_intensity'),
    ('Global_reactive_power', 'Sub_metering_1'),
]
```

```
nrows, ncols = 3, 2
fig, axes = plt.subplots(nrows, ncols, figsize=(20, 10))
axes = axes.flatten()
for ax, (x_col, y_col) in zip(axes, pairs):
    ax.scatter(newdf[x_col], newdf[y_col], marker='o', alpha=0.5)
    ax.set_title(f'{x_col} vs {y_col}')
    ax.set_xlabel(x_col)
    ax.set_ylabel(y_col)
    ax.grid(True)
plt.tight_layout()
plt.show()
```



Bar Chart

```
monthly_data = newdf.resample('ME').sum()
monthly_data[['Global_active_power', 'Global_reactive_power']].plot(kind='bar', figsize=(12, 6))
plt.title('Monthly Total of Global Active Power and Global Reactive Power')
plt.xlabel('Month')
plt.ylabel('Power (kW)')
plt.grid(True)
plt.show()
```



monthly_sub_metering = newdf[['Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3']].resample('ME').sum()

monthly_sub_metering.plot(*kind*='bar', *stacked*=True, *figsize*=(12, 6))

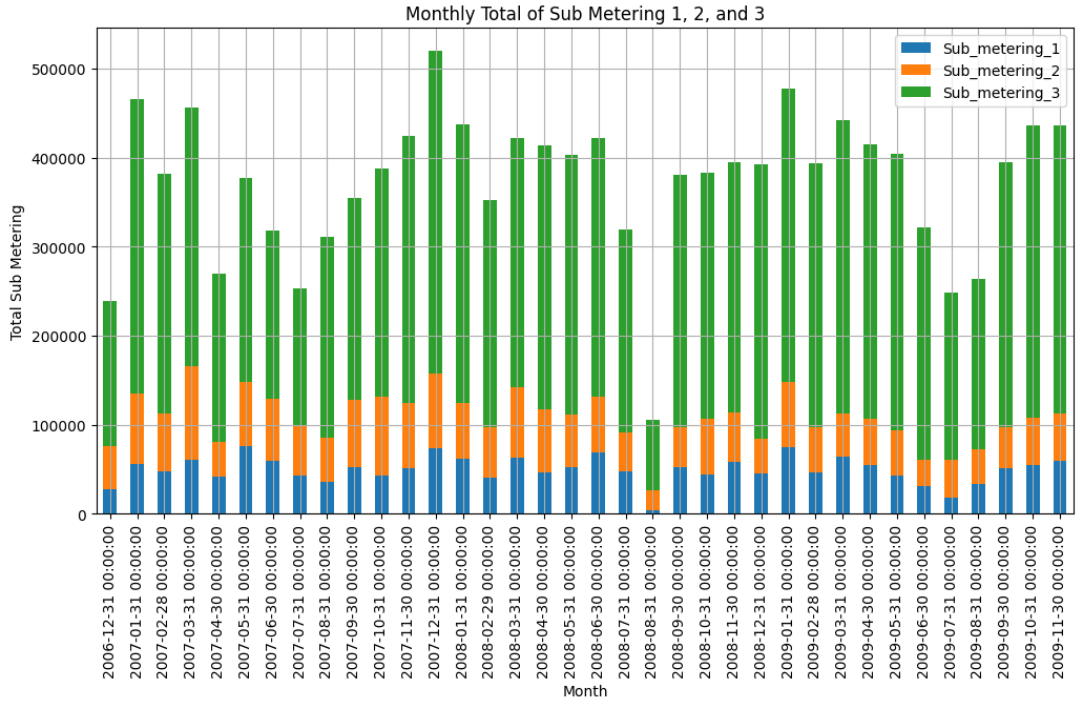
plt.title('Monthly Total of Sub Metering 1, 2, and 3')

plt.xlabel('Month')

plt.ylabel('Total Sub Metering')

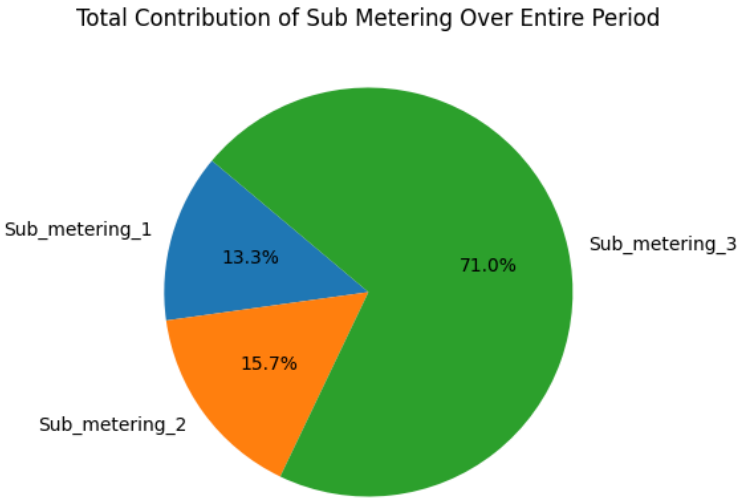
plt.grid(True)

plt.show()



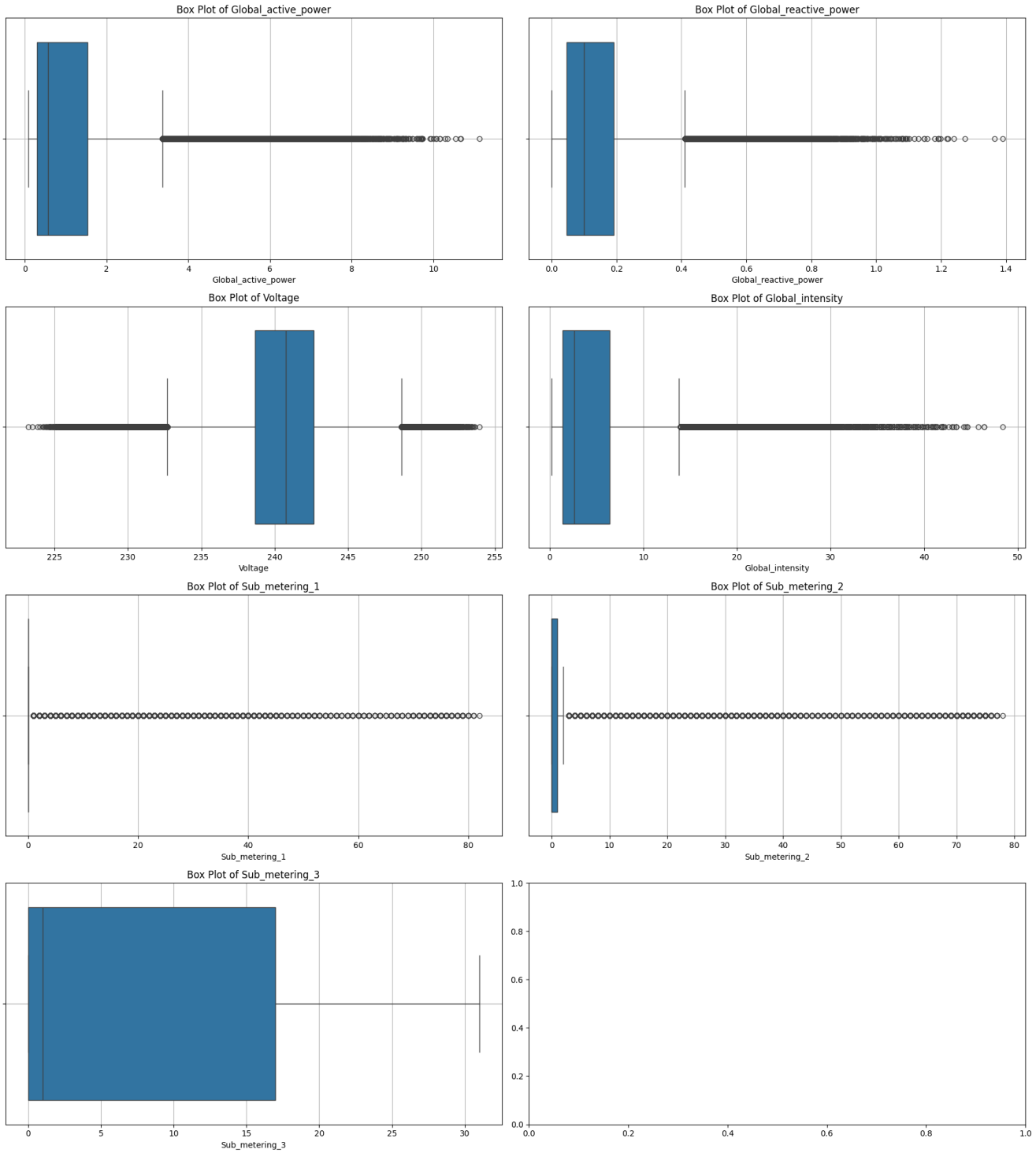
Pie Chart

```
total_sub_metering = monthly_sub_metering.sum()
plt.figure(figsize=(5, 5))
plt.pie(total_sub_metering, labels=total_sub_metering.index, autopct='%1.1f%%', startangle=140)
plt.title('Total Contribution of Sub Metering Over Entire Period')
plt.show()
```



Box Plot

```
columns_to_plot = ['Global_active_power', 'Global_reactive_power', 'Voltage',
                   'Global_intensity', 'Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3']
fig, axes = plt.subplots(nrows=4, ncols=2, figsize=(18, 20))
axes = axes.flatten()
for i, column in enumerate(columns_to_plot):
    sns.boxplot(x=newdf[column], ax=axes[i])
    axes[i].set_title(f'Box Plot of {column}')
    axes[i].grid(True)
plt.tight_layout()
plt.show()
```



Count Plot

hourly_data = newdf[['Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3']].resample('h').sum()

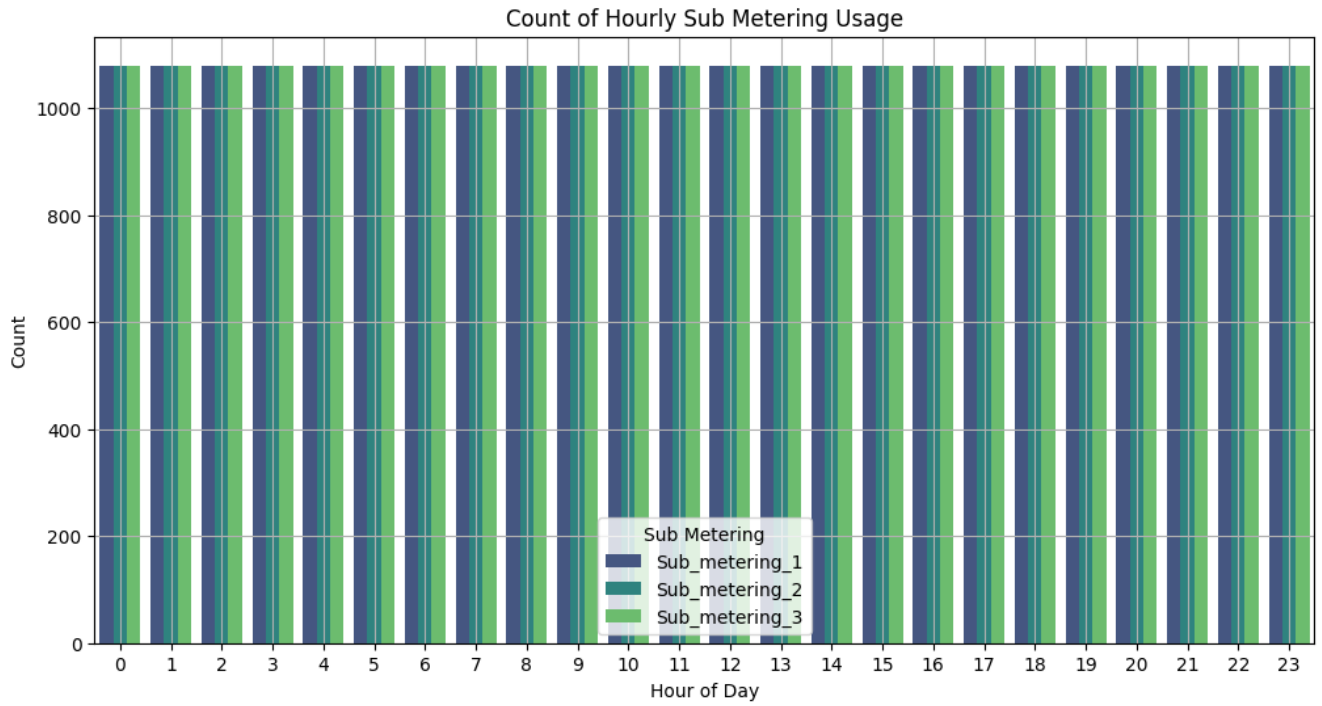
hourly_data['Hour'] = hourly_data.index.hour

hourly_data_melted = hourly_data.melt(*id_vars*='Hour', *var_name*='Sub_metering', *value_name*='Total')

plt.figure(*figsize*=(12, 6))

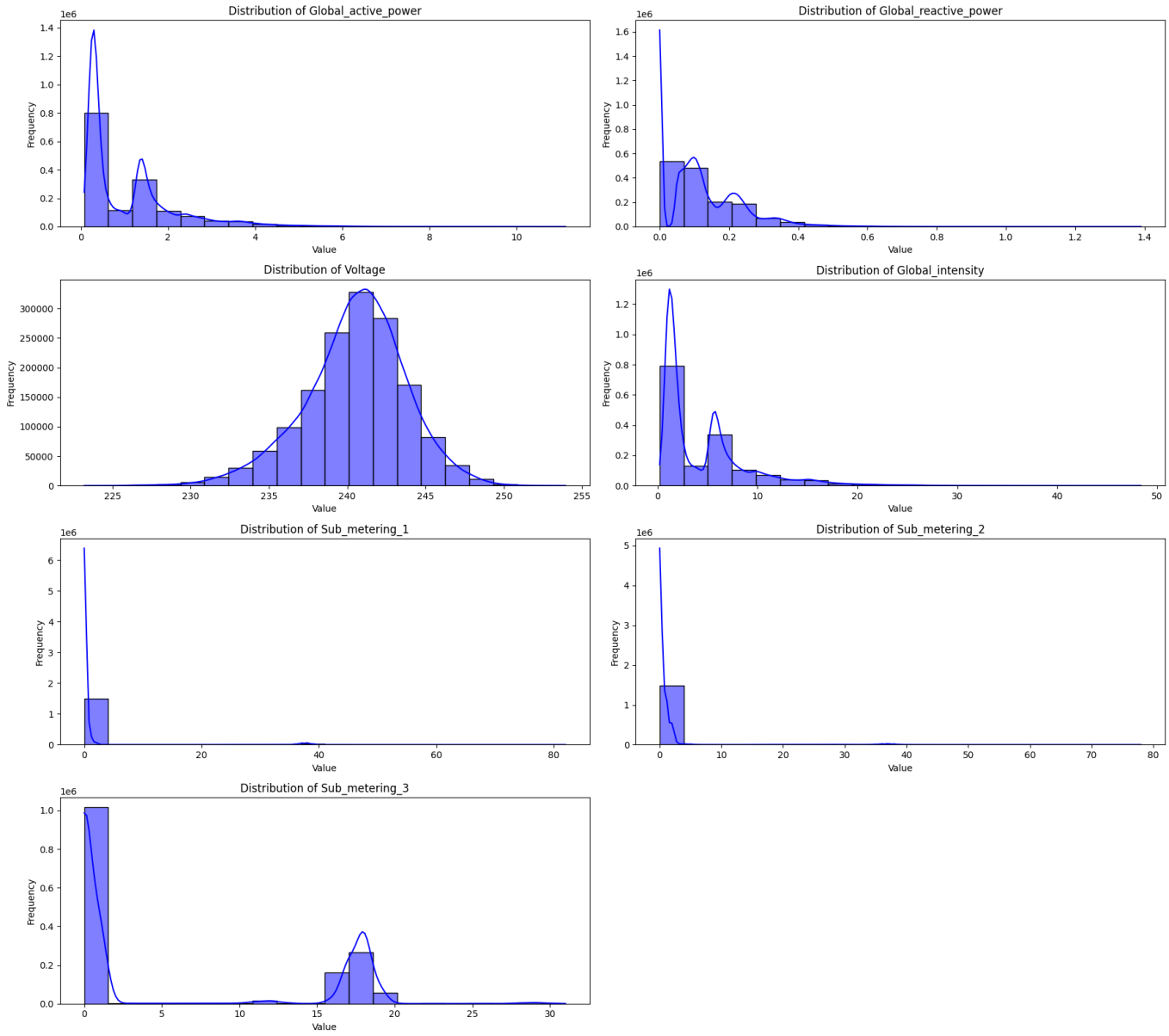
sns.countplot(*x*='Hour', *data*=hourly_data_melted, *hue*='Sub_metering', *palette*='viridis')

```
plt.title('Count of Hourly Sub Metering Usage')
plt.xlabel('Hour of Day')
plt.ylabel('Count')
plt.legend(title='Sub Metering')
plt.grid(True)
plt.show()
```



Distplot

```
columns_to_plot = ['Global_active_power', 'Global_reactive_power', 'Voltage',
                   'Global_intensity', 'Sub_metering_1', 'Sub_metering_2', 'Sub_metering_3']
plt.figure(figsize=(18, 16))
for i, column in enumerate(columns_to_plot):
    plt.subplot(4, 2, i + 1)
    sns.histplot(newdf[column], kde=True, color='blue', bins=20)
    plt.title(f'Distribution of {column}')
    plt.xlabel('Value')
    plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



Heatmap

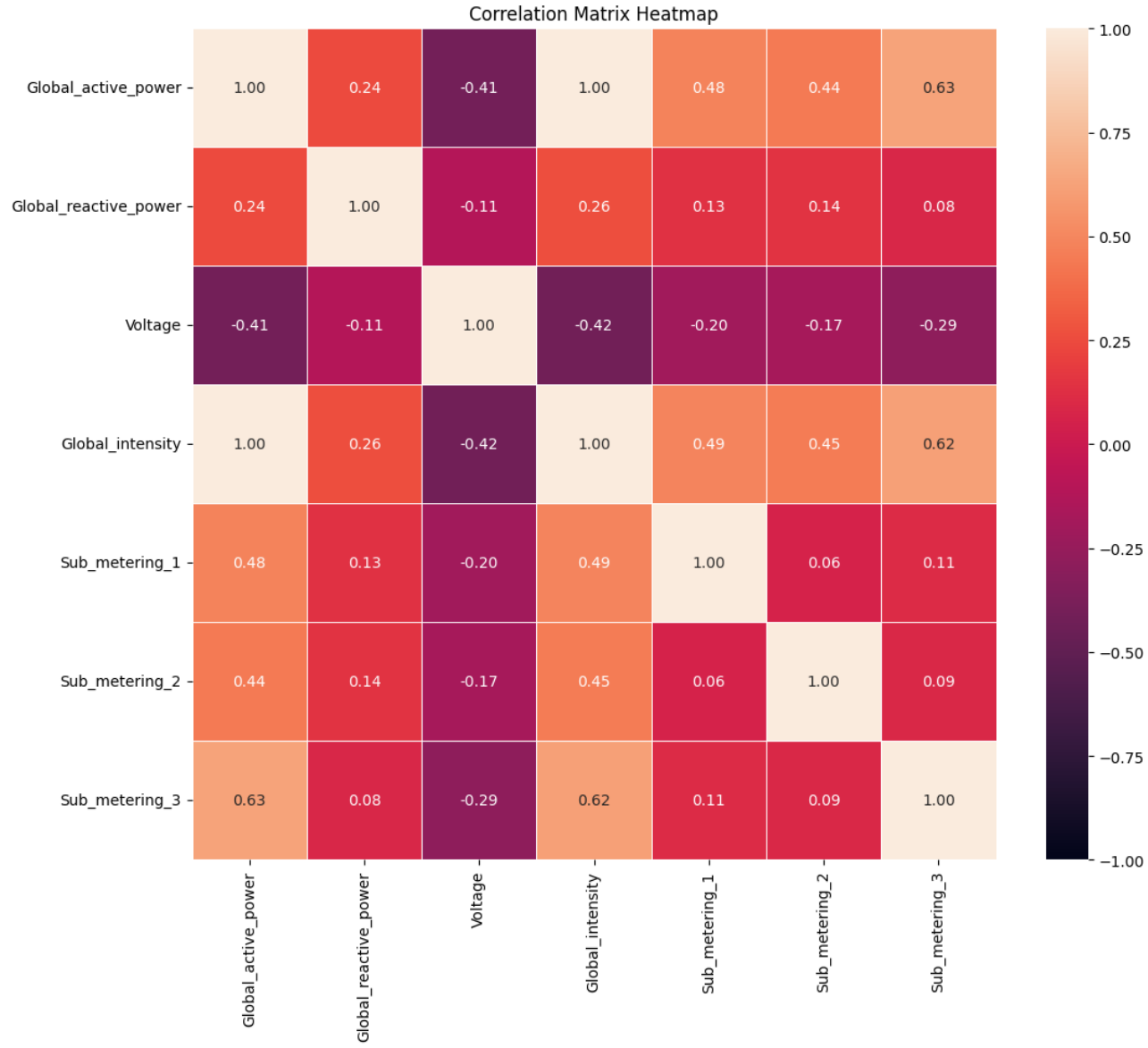
correlation_matrix = newdf.corr()

plt.figure(*figsize*=(12, 10))

sns.heatmap(correlation_matrix, *annot*=True, *fmt*='.2f', *linewidths*=0.5, *vmin*=-1, *vmax*=1)

plt.title('Correlation Matrix Heatmap')

plt.show()



Visualise Each Parameter Early

```
def visualize_yearly(data, feat_name):
    fig, axis = plt.subplots(4, 1, figsize=(30, 20))
    for i, d in enumerate(zip(axis, list(data[feat_name].groupby(data.index.year)))):
        d[0].plot(pd.DataFrame(d[1][1]), label=d[1][0])
        d[0].legend(loc='upper right')

    fig.text(0.40, 0.9, 'Year-Wise Analysis : %s ' % feat_name, va='center', fontdict={'fontsize': 25})
    plt.show()

visualize_yearly(data=newdf, feat_name='Global_active_power')
visualize_yearly(data=newdf, feat_name='Global_reactive_power')
```

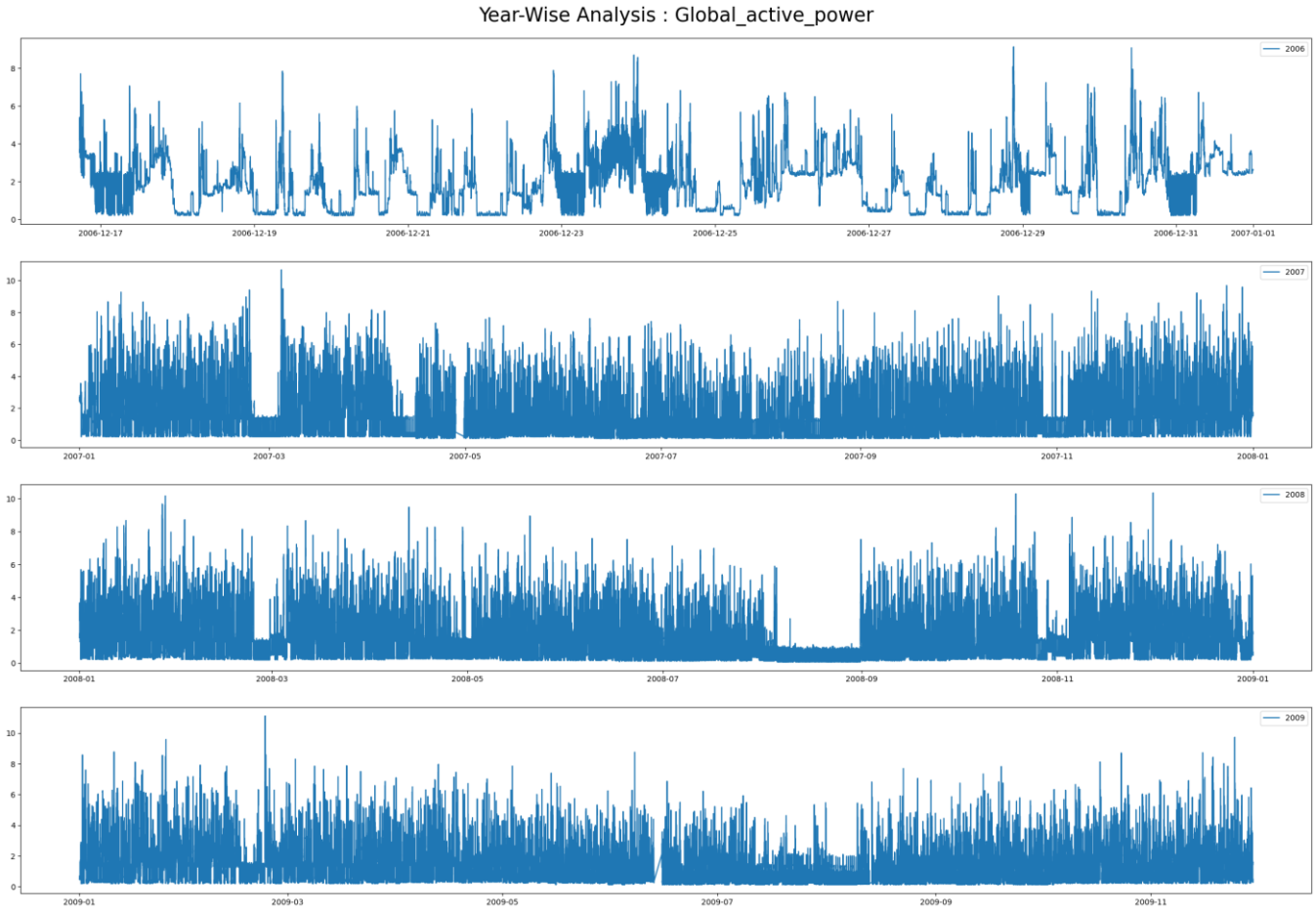
visualize_yearly(*data*=newdf, *feat_name*='Voltage')

visualize_yearly(*data*=newdf, *feat_name*='Global_intensity')

visualize_yearly(*data*=newdf, *feat_name*='Sub_metering_1')

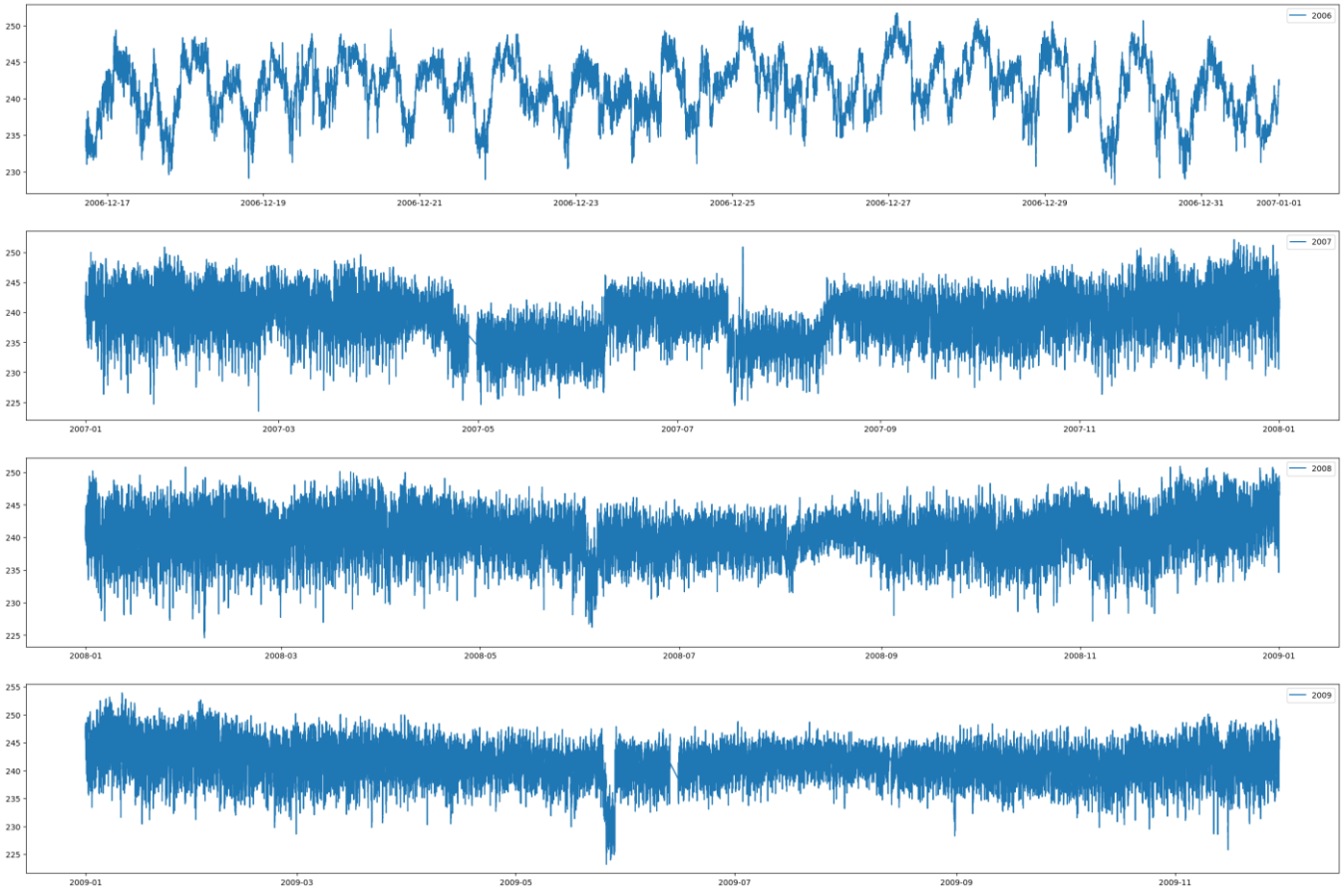
visualize_yearly(*data*=newdf, *feat_name*='Sub_metering_2')

visualize_yearly(*data*=newdf, *feat_name*='Sub_metering_3')

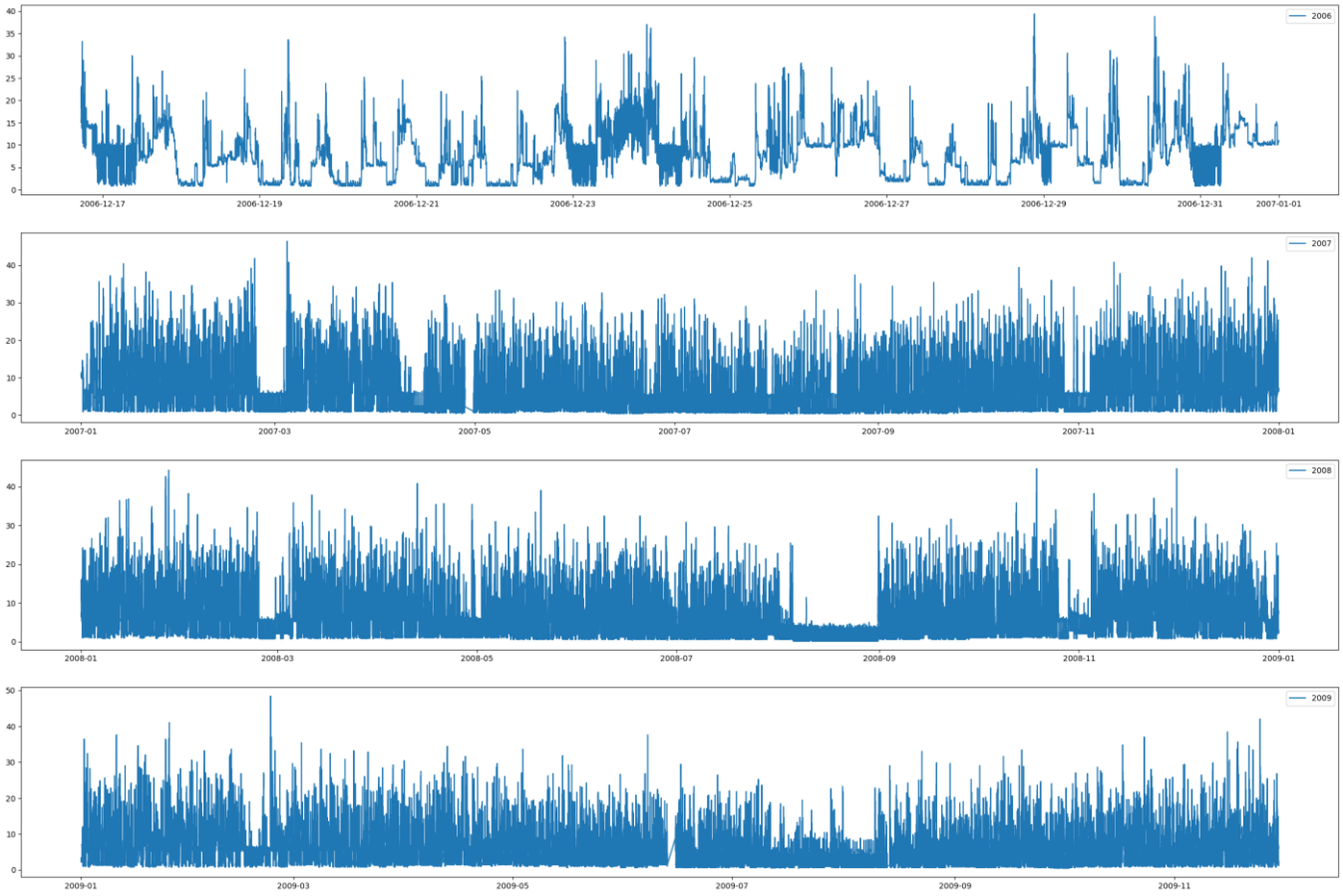


Year-Wise Analysis : Global_reactive_power

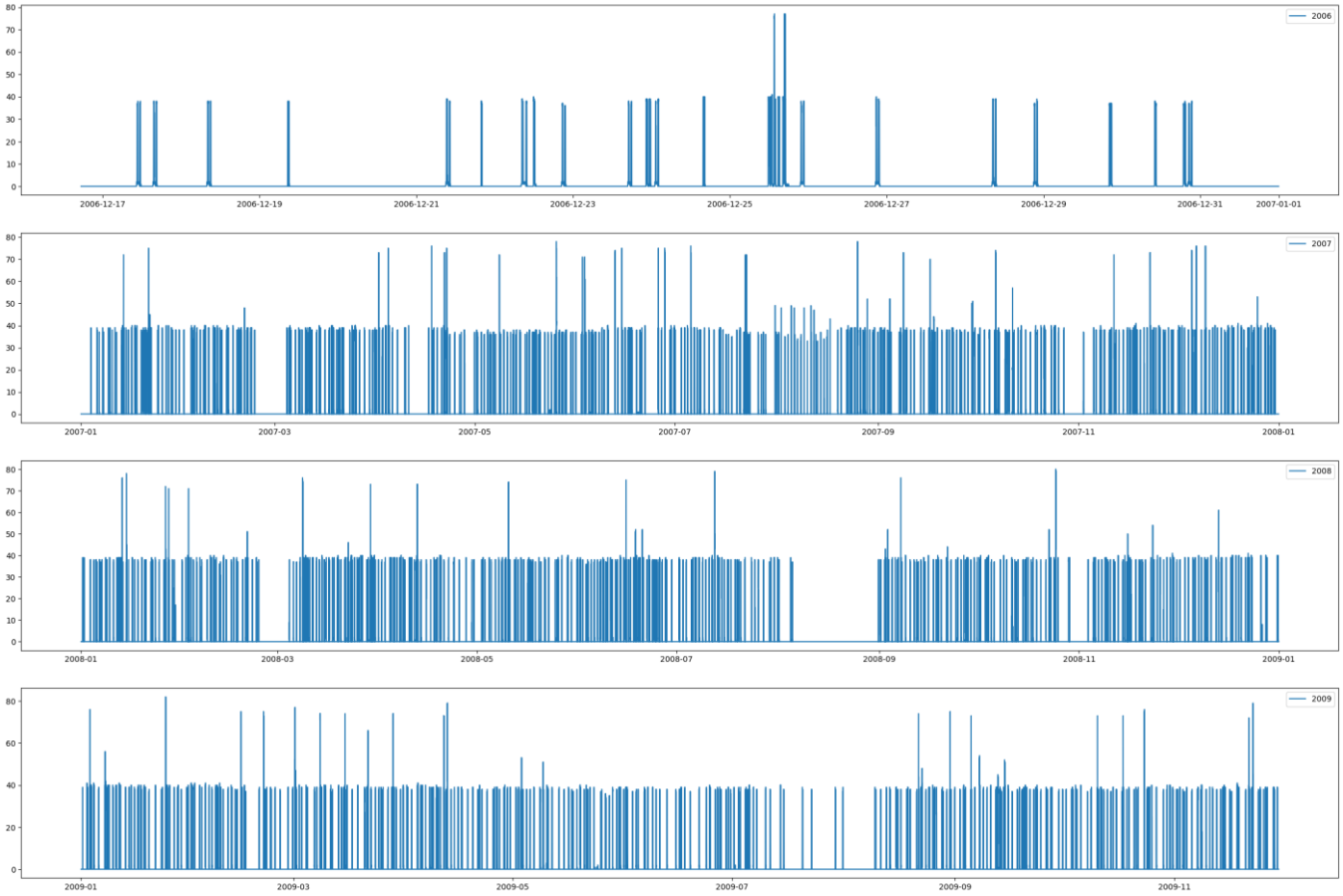
Year-Wise Analysis : Voltage



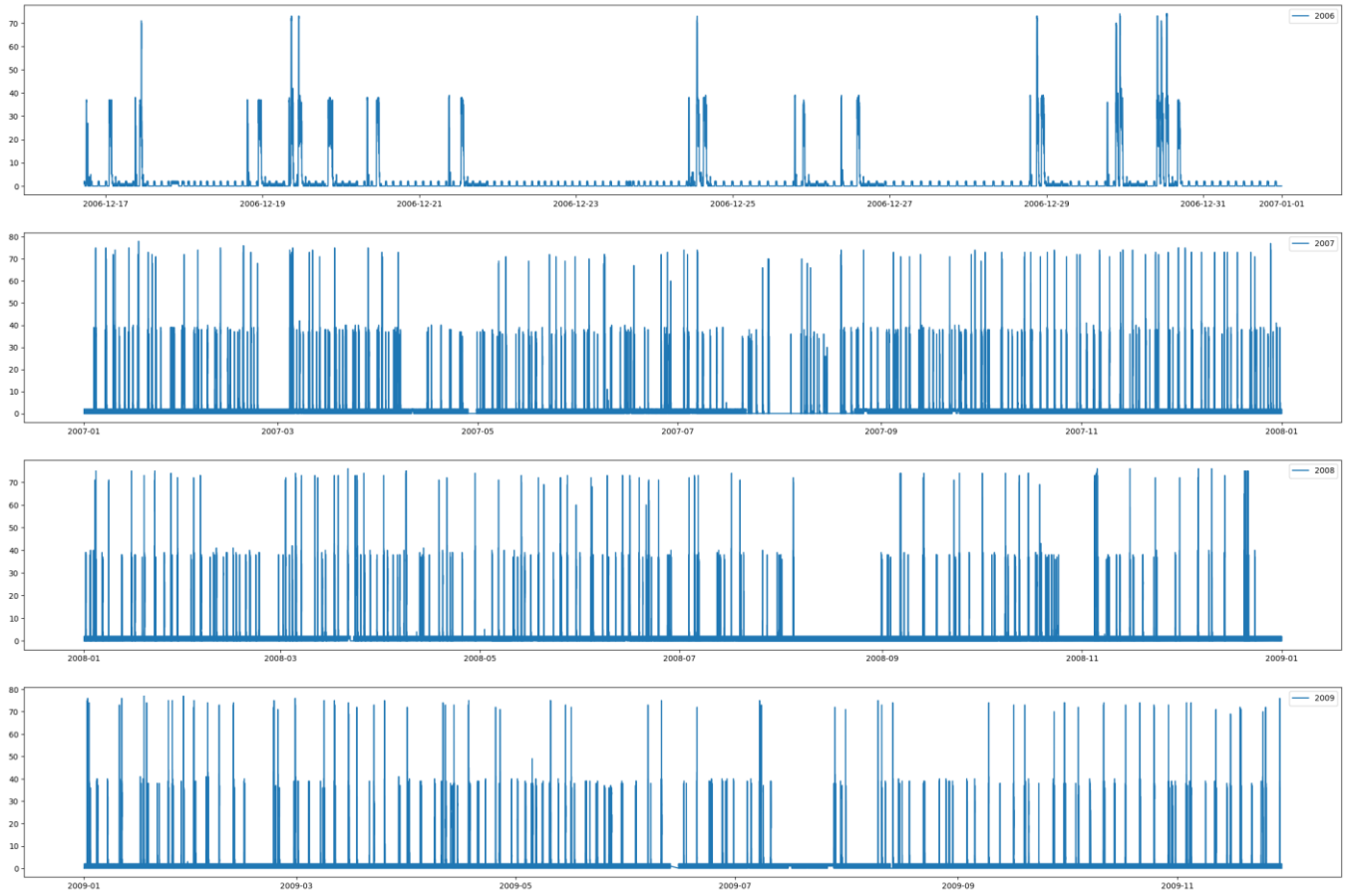
Year-Wise Analysis : Global_intensity



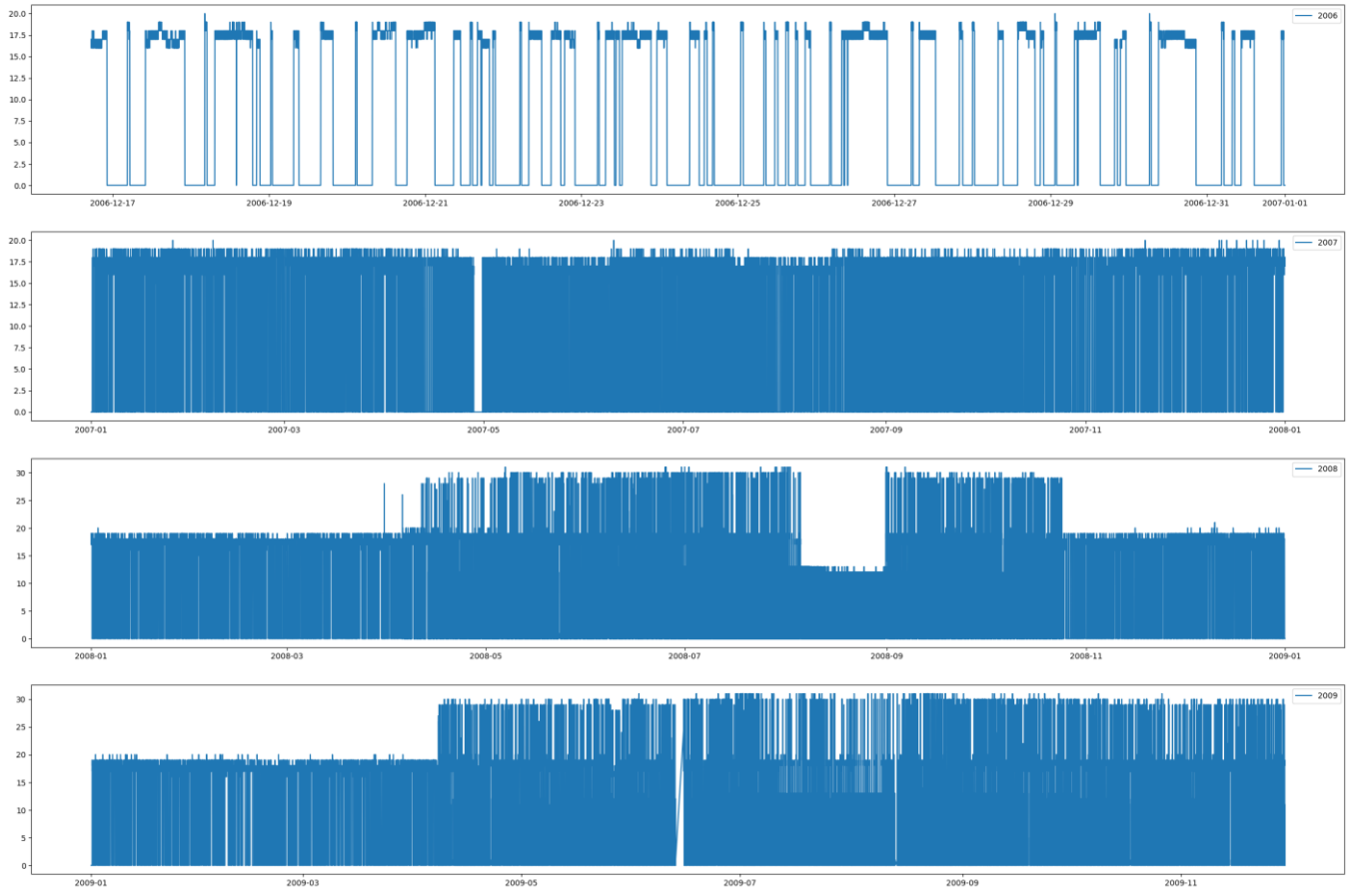
Year-Wise Analysis : Sub_metering_1



Year-Wise Analysis : Sub_metering_2



Year-Wise Analysis : Sub_metering_3



Use of each type of plot

- **Histogram**: Ideal for understanding the distribution of power consumption levels.
- **Time Series Plot**: Best for analysing trends and patterns over the 4-year period.
- **Plot for Sub Metering**: Key for comparing the contributions of different sub-meters over time.
- **Scatterplot**: Useful for examining relationships between two continuous variables.
- **Bar Chart**: Great for comparing quantities across different time periods.
- **Pie Chart**: Shows proportions of sub-metering contributions to total consumption.
- **Count Plot**: Displays the frequency of different power consumption categories.
- **Boxplot**: Summarizes distributions and highlights outliers in consumption data.
- **Heatmap**: Effective for identifying correlations and patterns across variables and time.
- **Distplot**: Combines a histogram and KDE to show a detailed distribution.

LAB ASSIGNMENT 3

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Implement simple and multi-linear regression to predict profits for a food truck. Compare the performance of the model on linear and multi-linear regression.		

Objective

The objective of this lab assignment is to implement simple and multi-linear regression models to predict profits for a food truck business. By comparing the performance of these two regression models, you will gain insights into when and how to use simple and multi-linear regression techniques.

Steps

1. **Data Preparation**:

   - Construct a numpy array containing both features (Population, Years in Business) and the target variable (Profit).
   - Separate the data into feature set XXX and target variable yyy.
   - Address any missing values in yyy by substituting NaN with the average of yyy.

2. **Simple Linear Regression**:

   - Develop a function called simple_linear_regression to compute the coefficients (β0\beta_0β0, β1\beta_1β1), make predictions, and calculate the mean squared error (MSE) for a single feature (Years in Business).
   - Extract the Years in Business as X_simple and apply the simple linear regression model.

3. **Multiple Linear Regression**:

   - Create a function named multi_linear_regression to determine coefficients, predictions, and MSE using all features.
   - Prepare the feature set X_multi by adding a column of ones for the intercept term and then perform the multiple linear regression analysis.

4. **Plotting**:

   - Generate two subplots:
     - The first subplot will display the results of the simple linear regression (Years in Business vs. Profit).
     - The second subplot will illustrate the results of the multiple linear regression (Population vs. Profit).
   - Show both actual and predicted values in these plots.

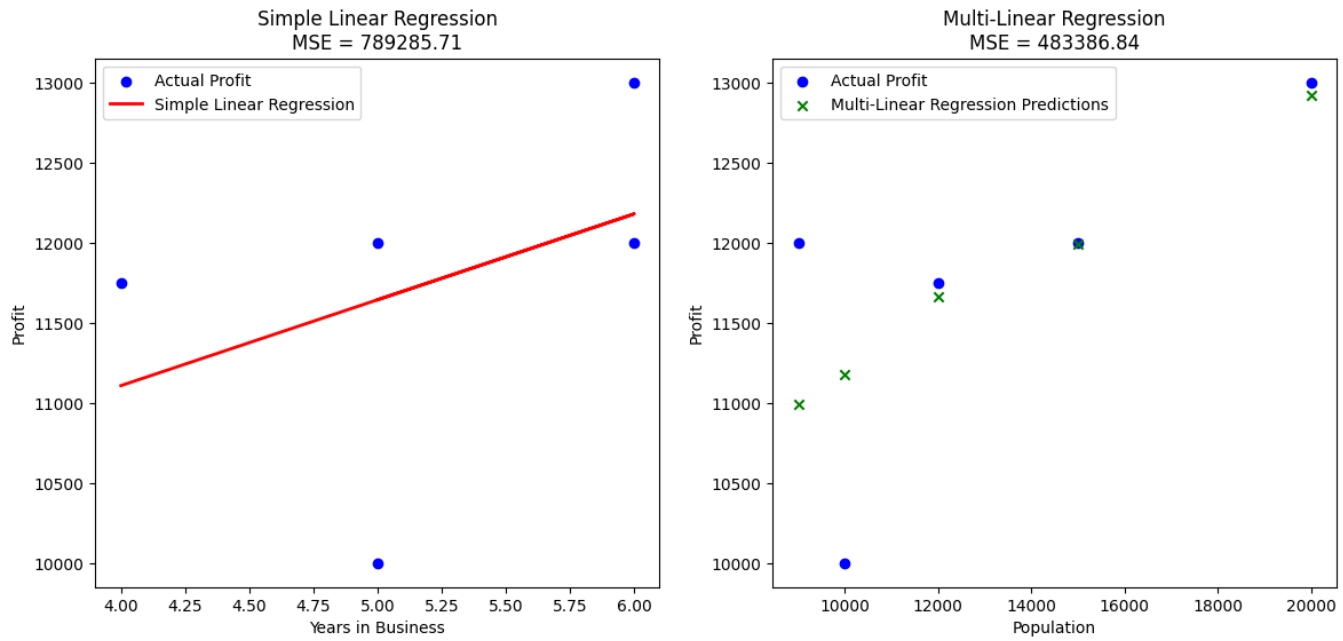
5. **Print Results**:

   - Print out the coefficients, intercepts, and MSE for both the simple and multiple linear regression models.

Code

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

data = np.array(
    [
        [10000, 5, 10000],
        [15000, 6, 12000],
        [20000, 6, 13000],
        [9000, 5, 12000],
        [12000, 4, np.nan],
    ]
)
X = data[:, :-1]
y = data[:, -1]

mean_y = np.nanmean(y)
y[np.isnan(y)] = mean_y


def simple_linear_regression(X_simple, y):
    X_simple_mean = np.mean(X_simple)
    y_mean = np.mean(y)
    beta1 = np.sum((X_simple - X_simple_mean) * (y - y_mean)) / np.sum(
        (X_simple - X_simple_mean) ** 2
    )
    beta0 = y_mean - beta1 * X_simple_mean
    y_pred = beta0 + beta1 * X_simple
    mse = np.mean((y - y_pred) ** 2)
    return beta0, beta1, y_pred, mse

def multi_linear_regression(X_multi, y):
    XTX = np.dot(X_multi.T, X_multi)
    XTX_inv = np.linalg.inv(XTX)
    XTy = np.dot(X_multi.T, y)
    beta = np.dot(XTX_inv, XTy)
    y_pred = np.dot(X_multi, beta)
    mse = np.mean((y - y_pred) ** 2)
    return beta, y_pred, mse


X_simple = X[:, 1]
beta0, beta1, y_pred_simple, mse_simple = simple_linear_regression(X_simple, y)
X_multi = np.hstack([np.ones((X.shape[0], 1)), X])
beta_multi, y_pred_multi, mse_multi = multi_linear_regression(X_multi, y)

plt.figure(figsize=(14, 6))

plt.subplot(1, 2, 1)
plt.scatter(X_simple, y, color="blue", label="Actual Profit")
plt.plot(
```

```
    X_simple, y_pred_simple, color="red", linewidth=2, label="Simple Linear Regression"
)
plt.xlabel("Years in Business")
plt.ylabel("Profit")
plt.title(f"Simple Linear Regression\nMSE = {mse_simple:.2f}")
plt.legend()

plt.subplot(1, 2, 2)
X_population = X[:, 0]
plt.scatter(X_population, y, color="blue", label="Actual Profit")
plt.scatter(
    X_population,
    y_pred_multi,
    color="green",
    marker="x",
    label="Multi-Linear Regression Predictions",
)
plt.xlabel("Population")
plt.ylabel("Profit")
plt.title(f"Multi-Linear Regression\nMSE = {mse_multi:.2f}")
plt.legend()
plt.show()
```

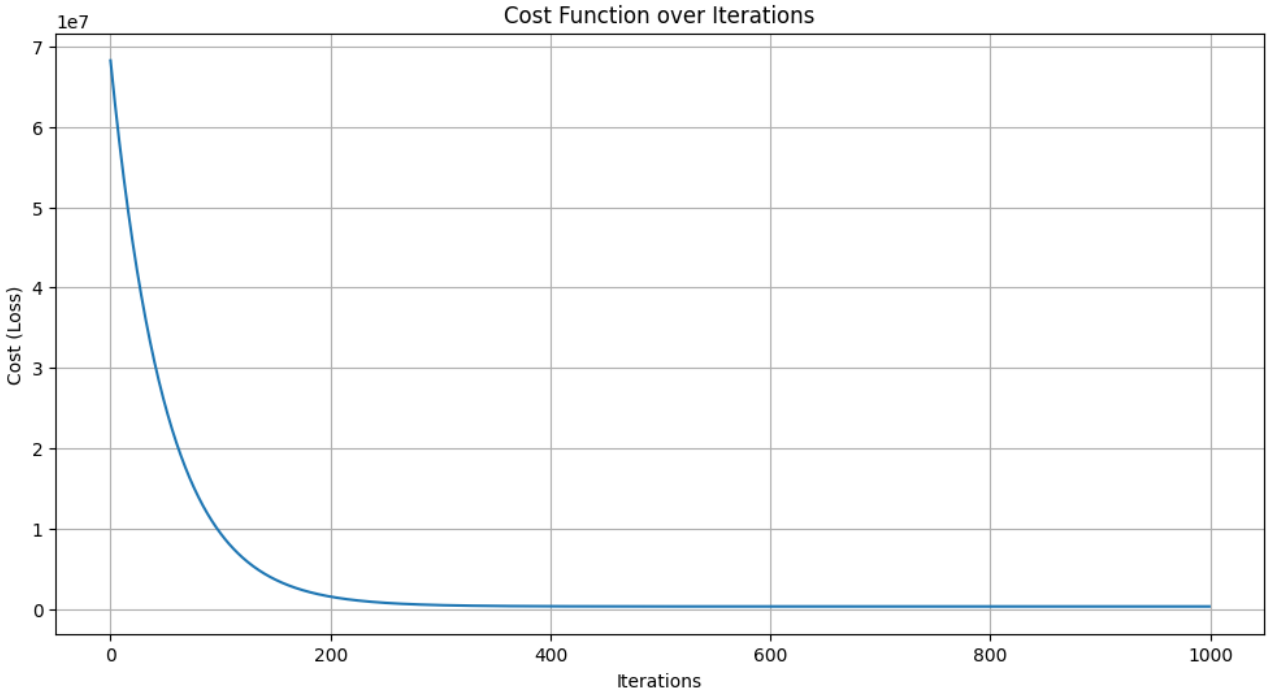



```
X = np.array([[10000], [15000], [20000], [9000]])
y = np.array([10000, 12000, 13000, 12000])

Population_mean = X.mean()
Population_std = X.std()
Population_normalized = (X - Population_mean) / Population_std

X = np.hstack((np.ones((X.shape[0], 1)), Population_normalized))
y = y
```

```
w = np.zeros(X.shape[1])

learning_rate = 0.01
n_iterations = 1000


def predict(X, w):
    return X.dot(w)

def compute_cost(X, y, w):
    m = len(y)
    predictions = predict(X, w)
    cost = (1 / (2 * m)) * np.sum((predictions - y) ** 2)
    return cost

def gradient_descent(X, y, w, learning_rate, n_iterations):
    m = len(y)
    cost_history = []

    for i in range(n_iterations):
        predictions = predict(X, w)
        errors = predictions - y
        gradients = (1 / m) * X.T.dot(errors)
        w -= learning_rate * gradients

        cost = compute_cost(X, y, w)
        cost_history.append(cost)

    return w, cost_history


w, cost_history = gradient_descent(X, y, w, learning_rate, n_iterations)

print(f"Final weights: {w}")

plt.figure(figsize=(12, 6))

plt.plot(range(len(cost_history)), cost_history)
plt.xlabel("Iterations")
plt.ylabel("Cost (Loss)")
plt.title("Cost Function over Iterations")
plt.grid(True)
plt.show()
```

Output

Final weights: [11749.49273784 769.20068232]



LAB ASSIGNMENT 4

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs		

Objective

To fit data points by assigning different weights to each point based on its proximity to the query point.

Dataset: Synthetic sinusoidal patterned data (Generated using *numpy* library)

Code

```
import numpy as np

import matplotlib.pyplot as plt


# Generate Dataset and splitting into features and target vars
```

We generate 80 random data points X uniformly distributed between 0 and 5. The target variable y is generated by taking the sine of X and adding some random noise to simulate real-world data.

```
np.random.seed(0)

X = np.sort(5 * np.random.rand(80, 1), axis=0)

y = np.sin(X).ravel() + np.random.normal(0, 0.1, X.shape[0])


# Normal Linear Regression

def normal_equation_linear_regression(X, y):
    m = X.shape[0]


    X_augmented = np.hstack([np.ones((m, 1)), X])


    XTX = np.dot(X_augmented.T, X_augmented)
    XTX_inv = np.linalg.pinv(XTX)
    theta = np.dot(XTX_inv, np.dot(X_augmented.T, y))
    return theta


theta = normal_equation_linear_regression(X, y)
```

```
def predict(X, theta):
    m = X.shape[0]
    X_augmented = np.hstack([np.ones((m, 1)), X])
    y_pred = np.dot(X_augmented, theta)
    return y_pred

y_pred = predict(X, theta)

plt.figure(figsize=(12, 8))
plt.scatter(X, y, label="Training Data", color="blue")
plt.plot(X, y_pred, color="red", linewidth=2, label="Linear Regression Fit")
plt.xlabel("X")
plt.ylabel("y")
plt.title("Normal Linear Regression")
plt.legend()
plt.show()

print(f"Intercept: {theta[0]}")
print(f"Coefficient: {theta[1]}")
```

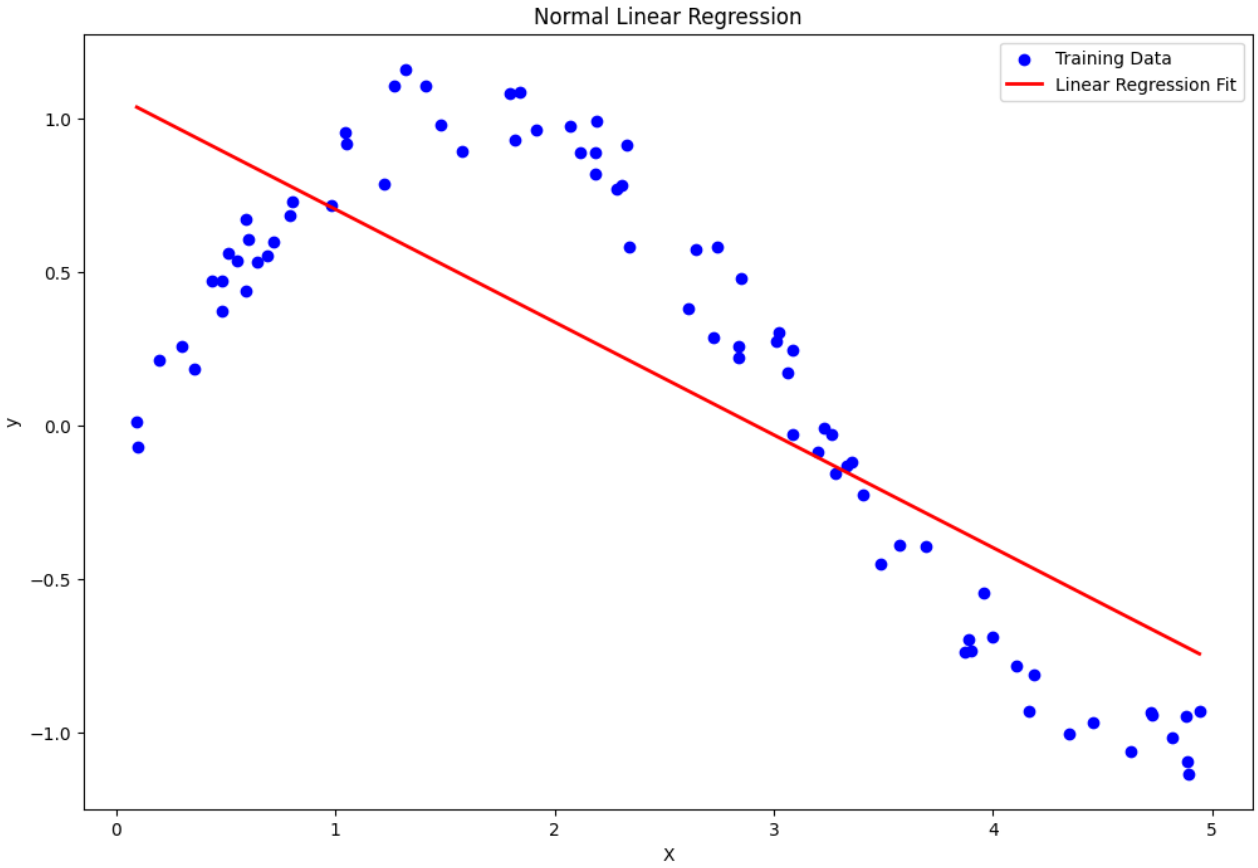
 # Implementation of Locally Weighted Regression algorithm

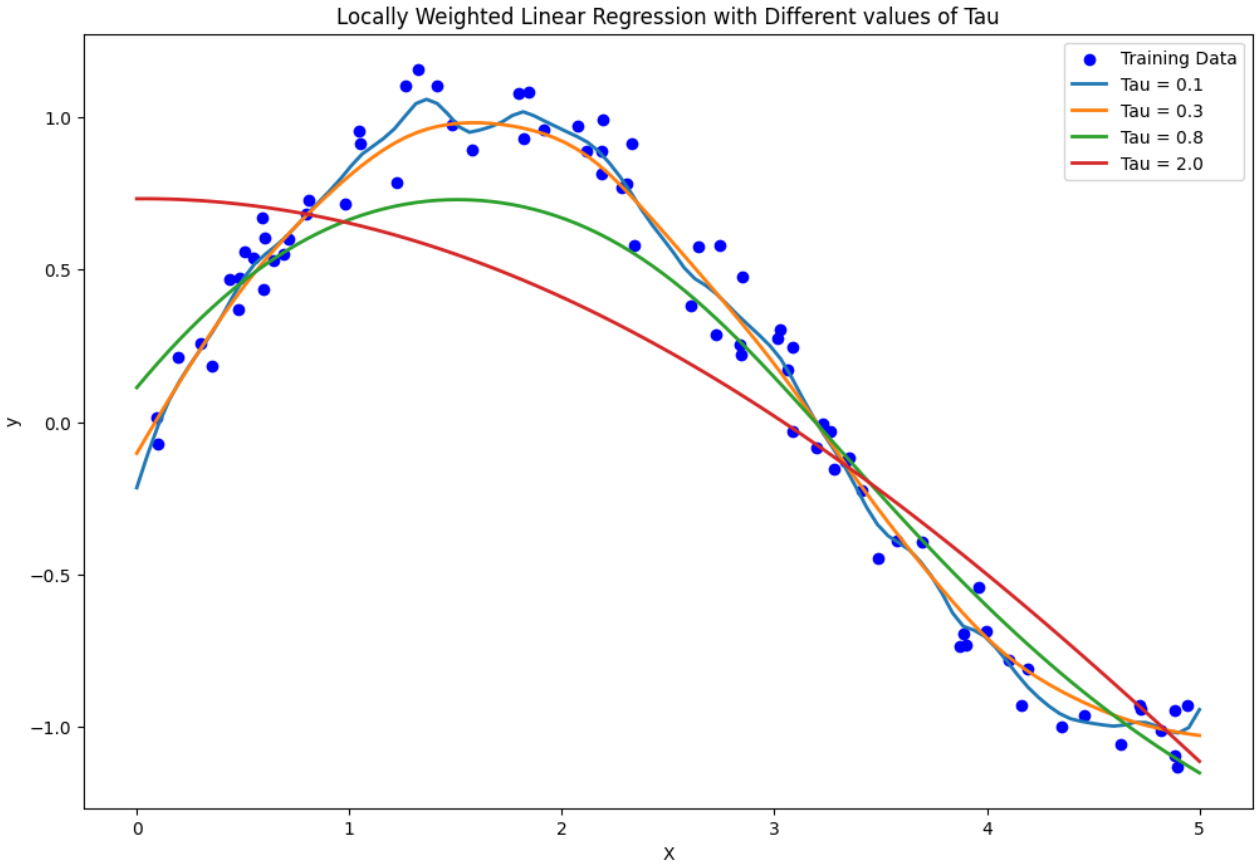
$$w^{(i)} = \exp\left(\frac{-\left(x^{(i)} - x\right)^2}{2\tau^2}\right) \qquad J(\theta) = \frac{1}{2}\sum_{i=1}^{m} w^{(i)}\left(\boldsymbol{\theta}^{\boldsymbol{T}} x^{(i)} - y^{(i)}\right)^2$$

```
def lwlr(X, y, x_query, tau):
    m = X.shape[0]
    W = np.exp(-np.sum((X - x_query) ** 2, axis=1) / (2 * tau**2))
    W = np.diag(W)

    X_augmented = np.hstack([np.ones((m, 1)), X])
    x_query_augmented = np.array([1, x_query.item()]).reshape(1, 2)
```

```
    XTWX = np.dot(np.dot(X_augmented.T, W), X_augmented)
    XTWy = np.dot(np.dot(X_augmented.T, W), y)
    theta = np.linalg.solve(XTWX, XTWy)
    y_query = np.dot(x_query_augmented, theta)
    return y_query

def predict_lwlr(X, y, X_query, tau):
    y_pred = np.array([lwlr(X, y, x_query, tau) for x_query in X_query])
    return y_pred

# Using Multiple Query Points
X_query = np.linspace(0, 5, 100).reshape(-1, 1)
taus = [0.1, 0.3, 0.8, 2.0]

predictions = {}
for tau in taus:
    predictions[tau] = predict_lwlr(X, y, X_query, tau)

# Plotting the Graph
plt.figure(figsize=(12, 8))
plt.scatter(X, y, label="Training Data", color="blue")
for tau in taus:
    plt.plot(X_query, predictions[tau], linewidth=2, label=f"Tau = {tau}")
plt.xlabel("X")
plt.ylabel("y")
plt.title("Locally Weighted Linear Regression with Different values of Tau")
plt.legend()
plt.show()
```

Output


Normal Linear Regression
Training Data
Linear Regression Fit
1.0
0.5
0.0
−0.5
−1.0
y
0
1
2
3
4
5
X


Locally Weighted Linear Regression with Different values of Tau
Training Data
Tau = 0.1
Tau = 0.3
Tau = 0.8
Tau = 2.0
1.0
0.5
0.0
−0.5
−1.0
y
0
1
2
3
4
5
X

LAB ASSIGNMENT 5

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	For a given set of training data examples stored in a .CSV file, implement and demonstrate various feature selection algorithms and compare the performance of the algorithms.		

Objective

The objective of this lab assignment is to implement and demonstrate various feature selection algorithms on a given training dataset stored in a .CSV file. The goal is to evaluate the effectiveness of these algorithms in terms of improving model accuracy and reducing dimensionality.

Code

```
import pandas as pd

import numpy as np

from sklearn.model_selection import KFold, cross_val_score

from sklearn.linear_model import LogisticRegression

from sklearn.model_selection import train_test_split

columns = ["Pregnancies", "GLucose", "BloodPressure", "Skin Thickness", "Insulin", "BMI", "DiabetesPedigreeFunction", "Age", "Outcome"]

dataset = pd.read_csv('./master_pima-indians-diabetes.csv')

dataset.head()

array = dataset.values

X = array[:, 0:8]

y = array[:, 8]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Univariate Analysis

```
from sklearn.feature_selection import SelectKBest

from sklearn.feature_selection import chi2


test = SelectKBest(score_func=chi2, k=4)

fit = test.fit(X, y)

np.set_printoptions(precision=3)
```

```
features = fit.transform(X)
print("Scores: ")
print(fit.scores_)
print("Features: ")
print(features[0:5, :])
```

```
Scores:
[ 110.727 1406.59    17.505   51.008 2219.398  127.671    5.356  178.011]
```

```
Features:
[[ 85.    0.   26.6  31. ]
 [183.    0.   23.3  32. ]
 [ 89.   94.   28.1  21. ]
 [137.  168.   43.1  33. ]
 [116.    0.   25.6  30. ]]
```

Recursive Feature Elimination

```
from sklearn.feature_selection import RFE
array = dataset.values
X = array[:, 0:8]
y = array[:, 8]
model = LogisticRegression()
rfe = RFE(model, n_features_to_select=4)
fit = rfe.fit(X,y)
print("Num Features: %d" % fit.n_features_)
print("Selected Features: %s" % fit.support_)
print("Feature Ranking: %s" % fit.ranking_)
reduced_dataset = dataset.iloc[:, :8].loc[:, fit.support_]
reduced_dataset.head()
```

```
Num Features: 4
Selected Features: [ True  True False False False  True  True False]
Feature Ranking: [1 1 3 5 4 1 1 2]
```

	6	148	33.6	0.627
0	1	85	26.6	0.351
1	8	183	23.3	0.672
2	1	89	28.1	0.167
3	0	137	43.1	2.288
4	5	116	25.6	0.201

Lasso - L1 Regularization

```
from sklearn.linear_model import Lasso
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
lasso = Lasso(alpha=0.05)
lasso.fit(X_train, y_train)
lasso_coefficients = lasso.coef_
selected_features = [feature for feature, coef in zip(columns, lasso_coefficients) if coef != 0]
print("Selected Features:", selected_features)
```

```
Selected Features: ['Pregnancies', 'GLucose', 'BloodPressure', 'Skin Thickness', 'BMI', 'Age']
```

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
rf_importances = rf_model.feature_importances_
sorted_indices = rf_importances.argsort()[::-1]
selected_features_rf = np.array(columns)[sorted_indices]
print("Feature Importances (Random Forest):")
for feature, importance in zip(selected_features_rf, rf_importances[sorted_indices]):
    print(f"{feature}: {importance:.4f}")
```

```
Feature Importances (Random Forest):
GLucose: 0.2590
BMI: 0.1503
Age: 0.1357
DiabetesPedigreeFunction: 0.1280
Pregnancies: 0.0976
BloodPressure: 0.0871
Insulin: 0.0768
Skin Thickness: 0.0655
```

XGBoost

```
import xgboost as xgb
xgb_model = xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss')
xgb_model.fit(X_train, y_train)
xgb_importances = xgb_model.feature_importances_
sorted_indices = xgb_importances.argsort()[::-1]
selected_features_xgb = np.array(columns)[sorted_indices]
print("Feature Importances (XGBoost):")
for feature, importance in zip(selected_features_xgb, xgb_importances[sorted_indices]):
    print(f"{feature}: {importance:.4f}")
```

```
Feature Importances (XGBoost):
GLucose: 0.2428
Age: 0.1437
BMI: 0.1319
Pregnancies: 0.1155
Skin Thickness: 0.1063
Insulin: 0.1061
DiabetesPedigreeFunction: 0.0844
BloodPressure: 0.0693
```

Comparing Random Forest with and without feature selection

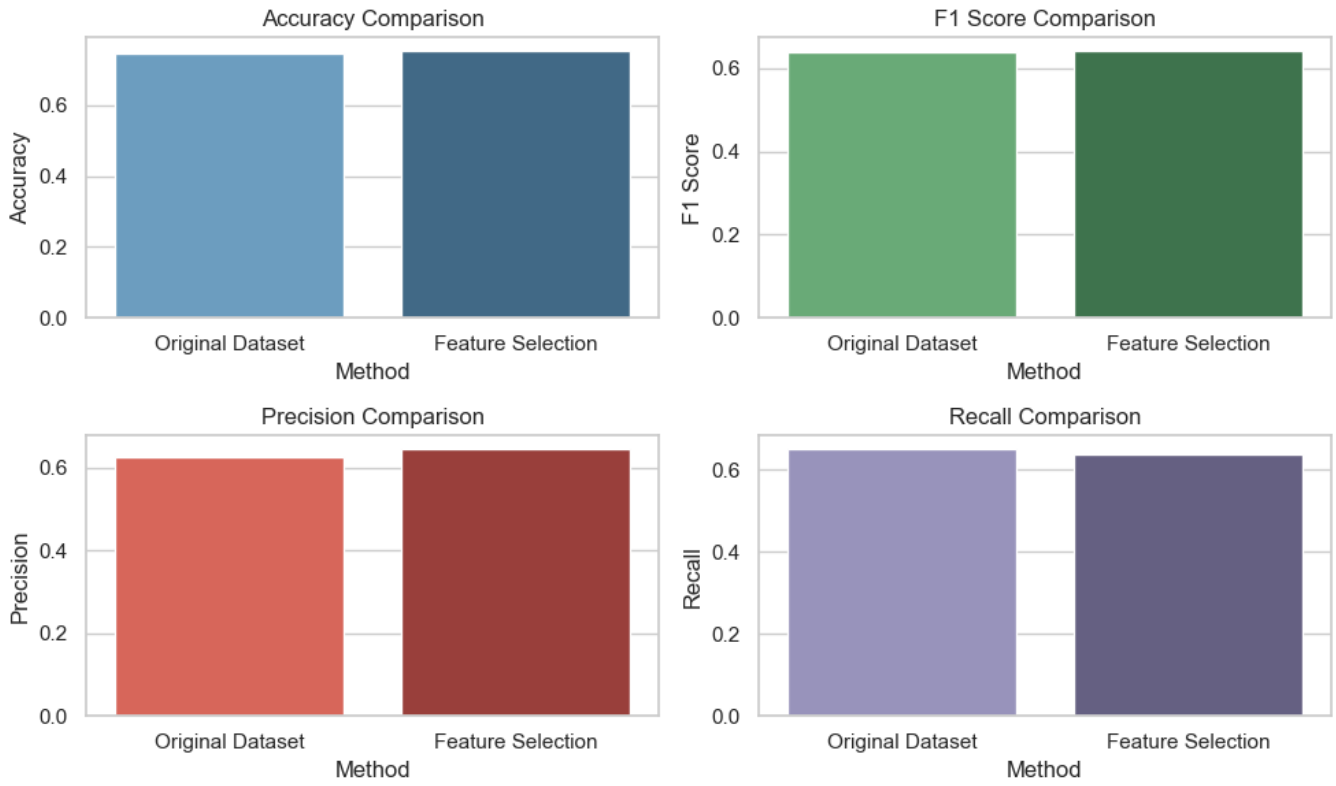
```
import xgboost as xgb
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score
from sklearn.ensemble import RandomForestClassifier

dataset = pd.read_csv('./master_pima-indians-diabetes.csv')
X = dataset.iloc[:, :-1]
y = dataset.iloc[:, -1]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# Step 1: Train XGBoost on the original dataset
xgb_model_original = xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss')
```

```
xgb_model_original.fit(X_train, y_train)
y_pred_original = xgb_model_original.predict(X_test)
accuracy_original = accuracy_score(y_test, y_pred_original)
f1_original = f1_score(y_test, y_pred_original)
precision_original = precision_score(y_test, y_pred_original)
recall_original = recall_score(y_test, y_pred_original)

# Step 2: Feature selection using Random Forest
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
rf_importances = rf_model.feature_importances_
sorted_indices = rf_importances.argsort()[::-1]
selected_features_rf = np.array(X.columns)[sorted_indices]
top_n = 5
X_train_selected = X_train[selected_features_rf[:top_n]]
X_test_selected = X_test[selected_features_rf[:top_n]]

# Step 3: Train XGBoost on the reduced dataset (with feature selection)
xgb_model_selected = xgb.XGBClassifier(use_label_encoder=False, eval_metric='logloss')
xgb_model_selected.fit(X_train_selected, y_train)
y_pred_selected = xgb_model_selected.predict(X_test_selected)
accuracy_selected = accuracy_score(y_test, y_pred_selected)
f1_selected = f1_score(y_test, y_pred_selected)
precision_selected = precision_score(y_test, y_pred_selected)
recall_selected = recall_score(y_test, y_pred_selected)
print("Performance on Original Dataset:")
print(f"Accuracy: {accuracy_original:.4f}, F1-Score: {f1_original:.4f}, Precision:
{precision_original:.4f}, Recall: {recall_original:.4f}")
print("\nPerformance on Reduced Dataset (With Feature Selection):")
print(f"Accuracy: {accuracy_selected:.4f}, F1-Score: {f1_selected:.4f}, Precision:
{precision_selected:.4f}, Recall: {recall_selected:.4f}")
```

Output - Visualisation

```
Performance on Original Dataset:
Accuracy: 0.7446, F1-Score: 0.6380, Precision: 0.6265, Recall: 0.6500
```

```
Performance on Reduced Dataset (With Feature Selection):
Accuracy: 0.7532, F1-Score: 0.6415, Precision: 0.6456, Recall: 0.6375
```



LAB ASSIGNMENT 6

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Apply Different Machine Learning Approaches for the Classification Task. Compare the Performance of Different ML Approaches in Terms of Accuracy, Precision, and Recall.		

Objective

The objective of this lab assignment is to apply various Machine Learning (ML) approaches to a classification task and compare their performance in terms of accuracy, precision, and recall. You will gain hands-on experience in implementing and evaluating different ML algorithms, understanding their strengths and weaknesses, and interpreting their results.

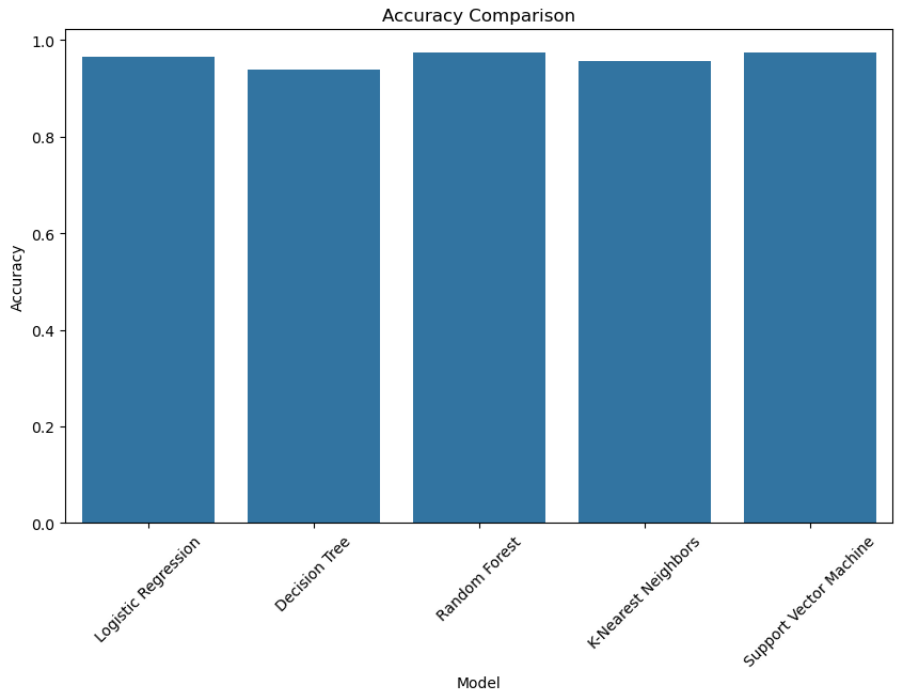
Code

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder

from sklearn.metrics import accuracy_score, precision_score, recall_score

from sklearn.linear_model import LogisticRegression

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier

from sklearn.neighbors import KNeighborsClassifier

from sklearn.preprocessing import StandardScaler

from sklearn.svm import SVC

import matplotlib.pyplot as plt

import seaborn as sns


data = pd.read_csv("data.csv")

data.head()

data_cleaned = data.drop(columns=["id", "Unnamed: 32"])

label_encoder = LabelEncoder()

data_cleaned["diagnosis"] = label_encoder.fit_transform(data_cleaned["diagnosis"])


X = data_cleaned.drop(columns=["diagnosis"])
```

```
y = data_cleaned["diagnosis"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
models = {
    "Logistic Regression": LogisticRegression(max_iter=10000),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
    "K-Nearest Neighbors": KNeighborsClassifier(),
    "Support Vector Machine": SVC(),
}

metrics = {"Model": [], "Accuracy": [], "Precision": [], "Recall": []}

for model_name, model in models.items():
    if model_name in [
        "Logistic Regression",
        "K-Nearest Neighbors",
        "Support Vector Machine",
    ]:
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_test_scaled)
    else:
        model.fit(X_train, y_train)
        y_pred = model.predict(X_test)

    metrics["Model"].append(model_name)
```

```
    metrics["Accuracy"].append(accuracy_score(y_test, y_pred))
    metrics["Precision"].append(precision_score(y_test, y_pred))
    metrics["Recall"].append(recall_score(y_test, y_pred))
metrics_df = pd.DataFrame(metrics)
print(metrics_df)


plt.figure(figsize=(10, 6))
sns.barplot(x="Model", y="Accuracy", data=metrics_df)
plt.title("Accuracy Comparison")
plt.xticks(rotation=45)
plt.show()
```

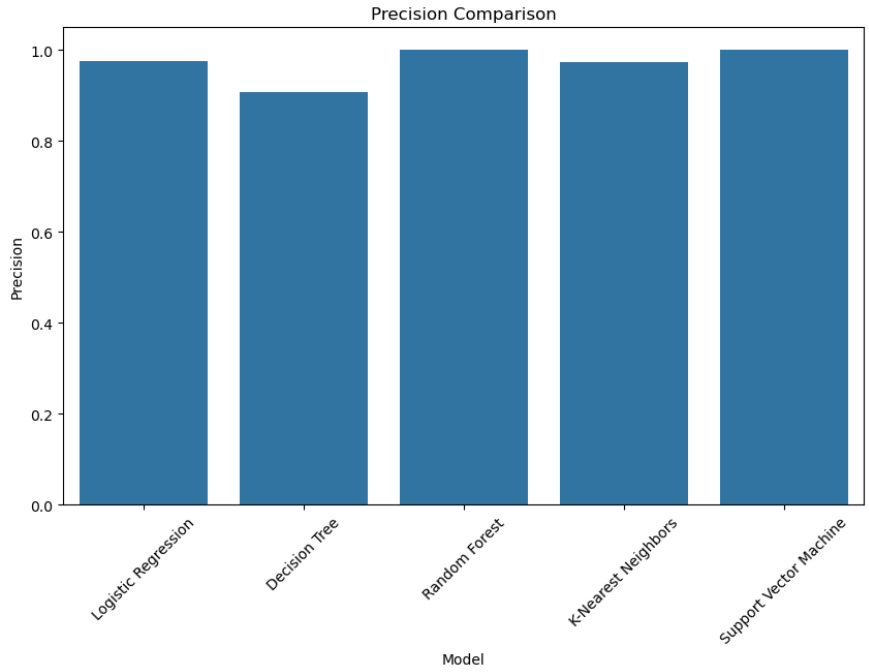
	Model	Accuracy	Precision	Recall
0	Logistic Regression	0.964912	0.975000	0.928571
1	Decision Tree	0.938596	0.906977	0.928571
2	Random Forest	0.973684	1.000000	0.928571
3	K-Nearest Neighbors	0.956140	0.974359	0.904762
4	Support Vector Machine	0.973684	1.000000	0.928571




```
plt.figure(figsize=(10, 6))
sns.barplot(x="Model", y="Precision", data=metrics_df)
plt.title("Precision Comparison")
```

plt.xticks(*rotation*=45)

plt.show()



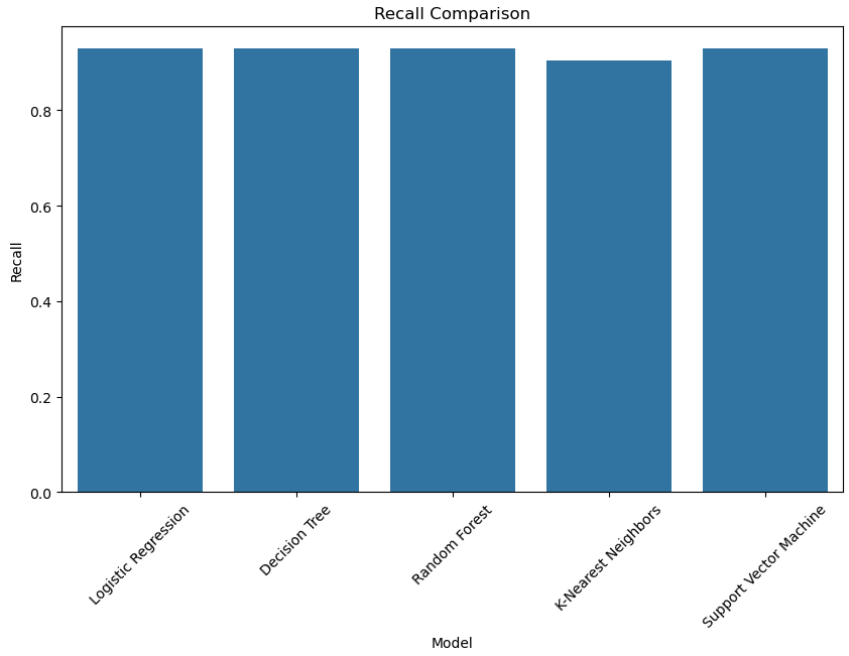
plt.figure(*figsize*=(10, 6))

sns.barplot(*x*="Model", *y*="Recall", *data*=metrics_df)

plt.title("Recall Comparison")

plt.xticks(*rotation*=45)

plt.show()



```
from sklearn.model_selection import GridSearchCV

param_grid = {
    "n_estimators": [50, 100, 150],
    "max_depth": [None, 10, 20, 30],
    "min_samples_split": [2, 5, 10],
}

grid_search = GridSearchCV(
    RandomForestClassifier(), param_grid, cv=5, scoring="accuracy"
)
grid_search.fit(X_train, y_train)

print("Best parameters for Random Forest:", grid_search.best_params_)
best_rf = grid_search.best_estimator_
y_pred_best_rf = best_rf.predict(X_test)

accuracy_best_rf = accuracy_score(y_test, y_pred_best_rf)
precision_best_rf = precision_score(y_test, y_pred_best_rf)
recall_best_rf = recall_score(y_test, y_pred_best_rf)

print(
    f"Best Random Forest - Accuracy: {accuracy_best_rf}, Precision: {precision_best_rf}, Recall: {recall_best_rf}"
)
```

Output

```
Best parameters for Random Forest: {'max_depth': 10, 'min_samples_split': 2, 'n_estimators': 50}
Best Random Forest - Accuracy: 0.9649122807017544, Precision: 1.0, Recall: 0.9047619047619048
```

LAB ASSIGNMENT 7

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Train a Machine Learning Classifier on an Imbalanced Dataset. Then Balance the Dataset Using Oversampling Techniques. Compare the Model Performance Before and After Oversampling.		

Objective

In this lab assignment, you will work with an imbalanced dataset and train a machine learning classifier on it. Afterward, you will apply oversampling techniques to balance the dataset and compare the model's performance before and after oversampling. The goal is to observe how oversampling affects the classifier's performance when dealing with imbalanced data.

Dataset: https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv

Code

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE
url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.csv"
column_names = [
    "Pregnancies",
    "Glucose",
    "BloodPressure",
    "SkinThickness",
    "Insulin",
    "BMI",
    "DiabetesPedigreeFunction",
    "Age",
    "Outcome",
]
```

```
data = pd.read_csv(url, names=column_names)
print("\nClass Distribution:\n", data["Outcome"].value_counts())
```

```
Class Distribution:
 Outcome
0    500
1    268
Name: count, dtype: int64
```

```
X = data.drop("Outcome", axis=1)
y = data["Outcome"]
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
clf = RandomForestClassifier(random_state=42)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print("\nBefore Oversampling:")
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
Before Oversampling:
[[85 15]
 [22 32]]
              precision    recall  f1-score   support

           0       0.79      0.85      0.82       100
           1       0.68      0.59      0.63        54

    accuracy                           0.76       154
   macro avg       0.74      0.72      0.73       154
weighted avg       0.75      0.76      0.76       154
```

```
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)
clf_smote = RandomForestClassifier(random_state=42)
clf_smote.fit(X_train_smote, y_train_smote)
y_pred_smote = clf_smote.predict(X_test)
print("\nAfter Oversampling (SMOTE):")
print(confusion_matrix(y_test, y_pred_smote))
print(classification_report(y_test, y_pred_smote))
```

```
After Oversampling (SMOTE):
[[74 26]
 [15 39]]
              precision    recall  f1-score   support

           0       0.83      0.74      0.78       100
           1       0.60      0.72      0.66        54

    accuracy                           0.73       154
   macro avg       0.72      0.73      0.72       154
weighted avg       0.75      0.73      0.74       154
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score


def evaluate_model(y_true, y_pred):
    accuracy = accuracy_score(y_true, y_pred)
    precision = precision_score(y_true, y_pred)
    recall = recall_score(y_true, y_pred)
    f1 = f1_score(y_true, y_pred)

    return {
        "accuracy": accuracy,
        "precision": precision,
        "recall": recall,
        "f1_score": f1,
    }
```

```
y_pred = clf.predict(X_test)
results_before = evaluate_model(y_test, y_pred)

y_pred_smote = clf_smote.predict(X_test)
results_after = evaluate_model(y_test, y_pred_smote)

print("\nPerformance Metrics Comparison:")
print(f"{'Metric':<15}{'Before Oversampling':<25}{'After Oversampling':<25}")
for metric in results_before.keys():
    print(
        f"{metric.capitalize():<15}{results_before[metric]:<25.4f}{results_after[metric]:<25.4f}"
    )
```

Output

```
Performance Metrics Comparison:
Metric         Before Oversampling      After Oversampling
Accuracy       0.7597                   0.7338
Precision      0.6809                   0.6000
Recall         0.5926                   0.7222
F1_score       0.6337                   0.6555
```

LAB ASSIGNMENT 8

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Apply Different Feature Selection Approaches for the Classification/Regression Task. Compare the Performance of Different Feature Selection Approaches.		

Objective

The objective of this lab assignment is to explore various feature selection techniques for classification and regression tasks.

Dataset: Use the UCI Iris dataset for the classification task and the Boston Housing dataset for the regression task.

Code

```
import numpy as np

import pandas as pd

from scipy.stats import chi2_contingency

class SelectKBest:

    def __init__(self, score_func, k='all'):

        self.score_func = score_func

        self.k = k

        self.scores_ = None

        self.selected_features_ = None


    def fit(self, X, y):

        y = y.ravel()

        self.scores_ = np.array([self.score_func(X.iloc[:, i], y) for i in range(X.shape[1])])


        if self.k == 'all':

            self.k = X.shape[1]

        self.selected_indices_ = np.argsort(self.scores_)[-self.k:]

        self.selected_features_ = X.columns[self.selected_indices_]


        return self
```

```
    def transform(self, X):
        return X.iloc[:, self.selected_indices_]

    def fit_transform(self, X, y):
        return self.fit(X, y).transform(X)

def chi2_score(x, y):
    contingency_table = pd.crosstab(x, y)
    chi2_stat, _, _, _ = chi2_contingency(contingency_table)
    return chi2_stat

from sklearn.base import BaseEstimator, RegressorMixin
from sklearn.utils import check_X_y, check_array
class RFE:
    def __init__(self, estimator, n_features_to_select=1):
        self.estimator = estimator
        self.n_features_to_select = n_features_to_select
        self.support_ = None
        self.ranking_ = None

    def fit(self, X, y):
        X, y = check_X_y(X, y)
        n_features = X.shape[1]
        self.ranking_ = np.zeros(n_features)

        while n_features > self.n_features_to_select:
            self.estimator.fit(X, y)
            importances = self.estimator.feature_importances_ if hasattr(self.estimator, 'feature_importances_')
else np.abs(self.estimator.coef_)
            worst_feature = np.argmin(importances)

            self.ranking_[worst_feature] += 1
```

```
            X = np.delete(X, worst_feature, axis=1)
            n_features -= 1

        self.support_ = np.where(self.ranking_ == 0)[0]
        return self

    def transform(self, X):
        return X.iloc[:, self.support_]

    def fit_transform(self, X, y):
        return self.fit(X, y).transform(X)

from sklearn.linear_model import Lasso
from sklearn.utils import check_X_y
class L1FeatureSelector:
    def __init__(self, alpha=1.0):
        self.alpha = alpha
        self.model = Lasso(alpha=self.alpha)
        self.selected_features_ = None

    def fit(self, X, y):
        X, y = check_X_y(X, y)
        self.model.fit(X, y)
        self.selected_features_ = np.where(self.model.coef_ != 0)[0]
        return self

    def transform(self, X):
        return X.iloc[:, self.selected_features_]

    def fit_transform(self, X, y):
        return self.fit(X, y).transform(X)
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.utils import check_X_y
class TreeBasedFeatureSelector:
    def __init__(self, n_estimators=100):
        self.n_estimators = n_estimators
        self.model = RandomForestClassifier(n_estimators=self.n_estimators)
        self.selected_features_ = None

    def fit(self, X, y):
        X, y = check_X_y(X, y)
        self.model.fit(X, y)
        importances = self.model.feature_importances_
        self.selected_features_ = np.where(importances > 0)[0]
        return self

    def transform(self, X):
        return X.iloc[:, self.selected_features_]

    def fit_transform(self, X, y):
        return self.fit(X, y).transform(X)

# Sample Data
import pandas as pd
from sklearn.datasets import load_iris

data = load_iris()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = data.target

# Univariate Feature Selection
selector_kbest = SelectKBest(score_func=chi2_score, k=2)
X_kbest = selector_kbest.fit_transform(X, y)
```

```
print("Selected Features (KBest):", selector_kbest.selected_features_)

# Recursive Feature Elimination
rfe_selector = RFE(estimator=RandomForestClassifier(), n_features_to_select=2)
X_rfe = rfe_selector.fit_transform(X, y)
print("Selected Features (RFE):", X.columns[rfe_selector.support_])

# L1-Based Feature Selection
l1_selector = L1FeatureSelector(alpha=0.1)
X_l1 = l1_selector.fit_transform(X, y)
print("Selected Features (L1):", X.columns[l1_selector.selected_features_])

# Tree-Based Feature Selection
tree_selector = TreeBasedFeatureSelector()
X_tree = tree_selector.fit_transform(X, y)
print("Selected Features (Tree-Based):", X.columns[tree_selector.selected_features_])
```

Output

```
Selected Features (KBest): Index(['petal width (cm)', 'petal length (cm)'], dtype='object')
Selected Features (RFE): Index(['petal length (cm)', 'petal width (cm)'], dtype='object')
Selected Features (L1): Index(['petal length (cm)'], dtype='object')
Selected Features (Tree-Based): Index(['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)',
       'petal width (cm)'],
      dtype='object')
```

LAB ASSIGNMENT 9

Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Write a Program to Demonstrate the Working of the Decision Tree-Based CART Algorithm. Build the Decision Tree and Classify a New Sample Using a Suitable Dataset. Compare the Performance with That of ID3, C4.5, and CART in Terms of Accuracy, Recall, Precision, and Sensitivity.		

Objective

The objective of this lab assignment is to implement the Decision Tree-based Classification and Regression Trees (CART) algorithm and compare its performance with other decision tree algorithms, namely ID3 and C4.5, in terms of accuracy, recall, precision, and sensitivity. The assignment includes building decision trees, classifying new samples, and evaluating the models using a suitable dataset.

Code

```
import numpy as np

import pandas as pd


class TreeNode:
    def __init__(self, feature_index=None, threshold=None, left=None, right=None, value=None):
        self.feature_index = feature_index
        self.threshold = threshold
        self.left = left
        self.right = right
        self.value = value


class CART:
    def fit(self, X, y):
        self.root = self._grow_tree(X, y)


    def _grow_tree(self, X, y):
        if len(set(y)) == 1:
            return TreeNode(value=y[0])


        best_gain = -float('inf')
```

```
        best_criteria = None
        best_sets = None

        n_samples, n_features = X.shape
        for feature_index in range(n_features):
            thresholds = np.unique(X[:, feature_index])
            for threshold in thresholds:
                left_indices = X[:, feature_index] <= threshold
                right_indices = X[:, feature_index] > threshold

                if len(y[left_indices]) == 0 or len(y[right_indices]) == 0:
                    continue

                gain = self._gini_gain(y, left_indices, right_indices)
                if gain > best_gain:
                    best_gain = gain
                    best_criteria = (feature_index, threshold)
                    best_sets = (left_indices, right_indices)

        if best_gain == -float('inf'):
            return TreeNode(value=np.bincount(y).argmax())

        left_node = self._grow_tree(X[best_sets[0]], y[best_sets[0]])
        right_node = self._grow_tree(X[best_sets[1]], y[best_sets[1]])
            return TreeNode(feature_index=best_criteria[0], threshold=best_criteria[1], left=left_node,
right=right_node)

    def _gini_gain(self, y, left_indices, right_indices):
        parent_impurity = self._gini_impurity(y)
        left_impurity = self._gini_impurity(y[left_indices])
        right_impurity = self._gini_impurity(y[right_indices])
        n = len(y)
```

```
        n_left = len(y[left_indices])
        n_right = len(y[right_indices])
        weighted_child_impurity = (n_left / n) * left_impurity + (n_right / n) * right_impurity
        return parent_impurity - weighted_child_impurity

    def _gini_impurity(self, y):
        class_counts = np.bincount(y)
        return 1.0 - np.sum((class_counts / len(y)) ** 2)

    def predict(self, X):
        return [self._predict(inputs) for inputs in X]

    def _predict(self, inputs):
        node = self.root
        while node.value is None:
            if inputs[node.feature_index] <= node.threshold:
                node = node.left
            else:
                node = node.right
        return node.value

from sklearn.tree import DecisionTreeClassifier

def build_id3(X_train, y_train):
    model = DecisionTreeClassifier(criterion='entropy')  # ID3 uses entropy
    model.fit(X_train, y_train)
    return model

def build_c45(X_train, y_train):
    model = DecisionTreeClassifier(criterion='gini')  # C4.5 uses Gini impurity
    model.fit(X_train, y_train)
    return model
```

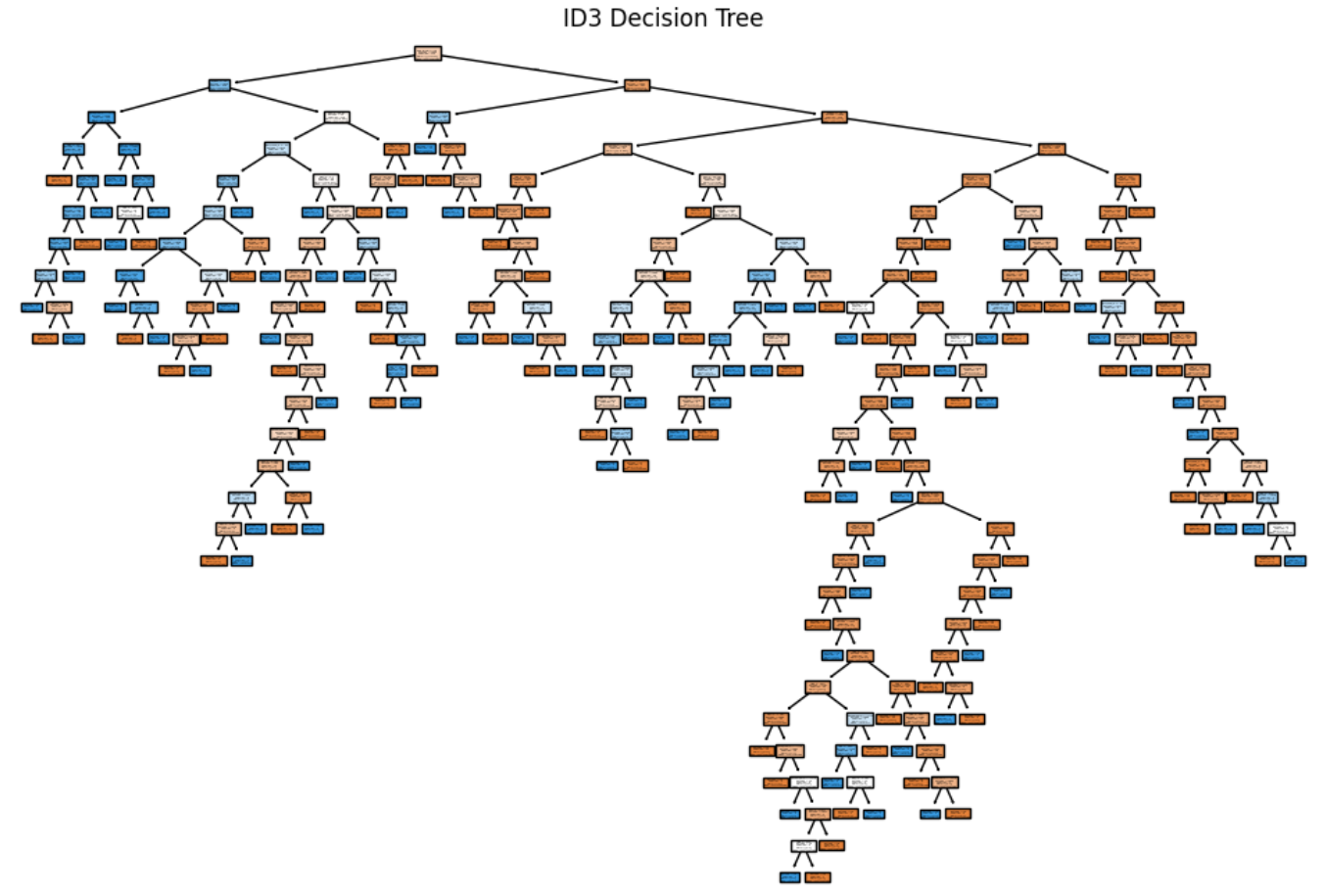
```
from sklearn.metrics import accuracy_score, recall_score, precision_score, confusion_matrix

def evaluate_model(model, X_test, y_test):
    y_pred = model.predict(X_test) if hasattr(model, 'predict') else model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)

    # Confusion matrix
    tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
    sensitivity = tp / (tp + fn) if (tp + fn) > 0 else 0  # Avoid division by zero

    return accuracy, recall, precision, sensitivity

from sklearn.model_selection import train_test_split

def load_titanic_dataset():
    url = "https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv"
    data = pd.read_csv(url)

    # Preprocess the data: drop rows with missing target and fill missing values
    data = data.drop(columns=["Name", "Ticket", "Cabin"])  # Drop non-feature columns
    data['Embarked'] = data['Embarked'].fillna('S')  # Fill missing Embarked
    data['Age'] = data['Age'].fillna(data['Age'].median())  # Fill missing Age with median
    data['Fare'] = data['Fare'].fillna(data['Fare'].median())  # Fill missing Fare with median

    # Convert categorical variables to dummy variables
    data = pd.get_dummies(data, columns=["Sex", "Embarked"], drop_first=True)

    X = data.drop("Survived", axis=1)  # Features
    y = data["Survived"]  # Target labels
```

```
    return train_test_split(X, y, test_size=0.2, random_state=42)


import matplotlib.pyplot as plt
from sklearn.tree import plot_tree


def compare_models():
    X_train, X_test, y_train, y_test = load_titanic_dataset()

    # Implement CART from scratch
    cart_model = CART()
    cart_model.fit(X_train.to_numpy(), y_train.to_numpy())

    # Using scikit-learn for ID3 and C4.5
    id3_model = build_id3(X_train, y_train)
    c45_model = build_c45(X_train, y_train)

    # Evaluate models
    cart_metrics = evaluate_model(cart_model, X_test.to_numpy(), y_test.to_numpy())
    id3_metrics = evaluate_model(id3_model, X_test, y_test)
    c45_metrics = evaluate_model(c45_model, X_test, y_test)

    # Print comparison
    print("CART Metrics (Accuracy, Recall, Precision, Sensitivity):", cart_metrics)
    print("ID3 Metrics (Accuracy, Recall, Precision, Sensitivity):", id3_metrics)
    print("C4.5 Metrics (Accuracy, Recall, Precision, Sensitivity):", c45_metrics)

    # Visualize the CART tree
    plt.figure(figsize=(12, 8))
      plot_tree(id3_model, filled=True, feature_names=X_train.columns, class_names=['Not Survived',
'Survived'])
    plt.title("ID3 Decision Tree")
    plt.show()
```

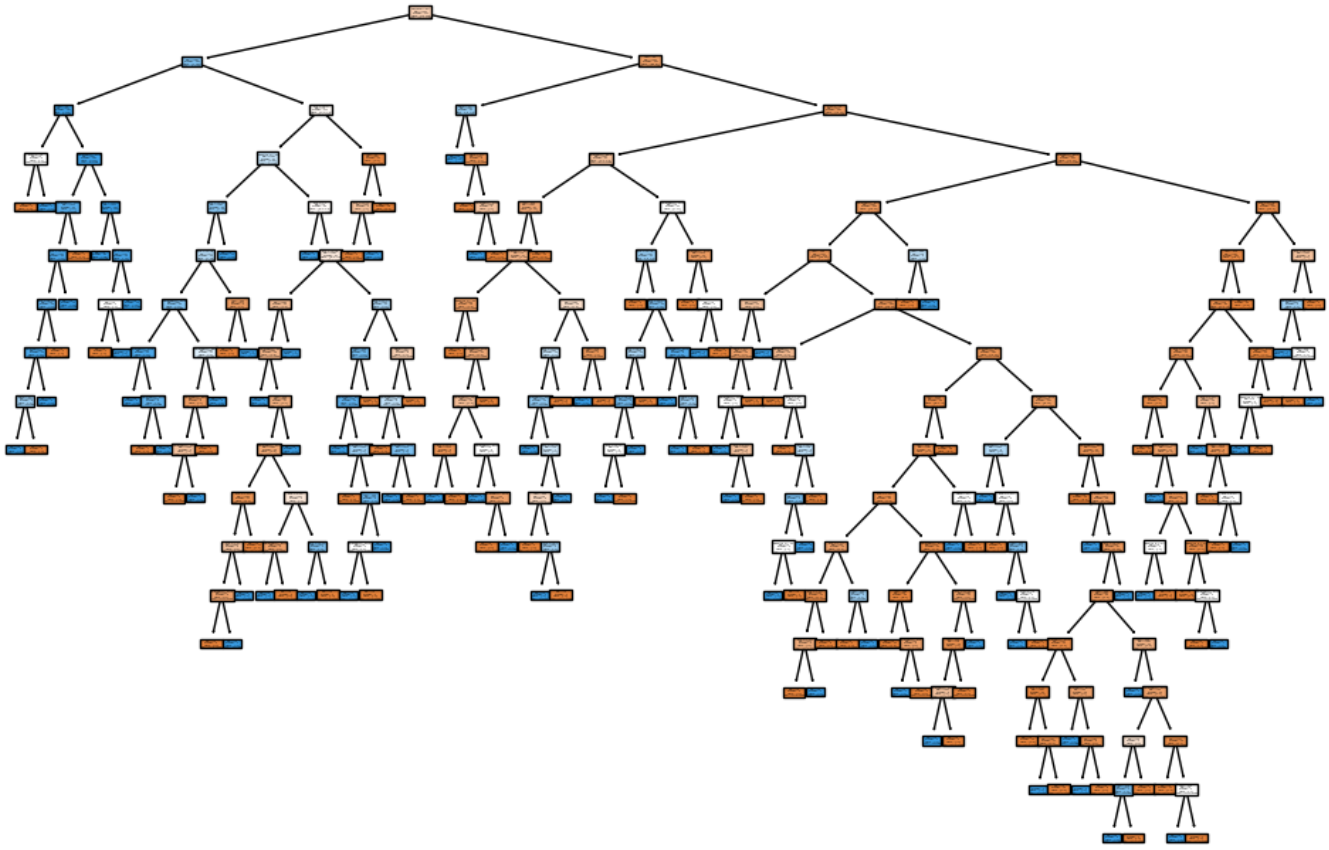
```
    plt.figure(figsize=(12, 8))
     plot_tree(c45_model, filled=True, feature_names=X_train.columns, class_names=['Not Survived', 'Survived'])
    plt.title("C4.5 Decision Tree")
    plt.show()

# Run the comparison
compare_models()
```

Output

```
CART Metrics (Accuracy, Recall, Precision, Sensitivity): (0.6927374301675978, 0.6891891891891891, 0.6144578313253012, 0.6891891891891891)
ID3 Metrics (Accuracy, Recall, Precision, Sensitivity): (0.7262569832402235, 0.6891891891891891, 0.6623376623376623, 0.6891891891891891)
C4.5 Metrics (Accuracy, Recall, Precision, Sensitivity): (0.7262569832402235, 0.6756756756756757, 0.6666666666666666, 0.6756756756756757)
```



C4.5 Decision Tree



LAB ASSIGNMENT 10

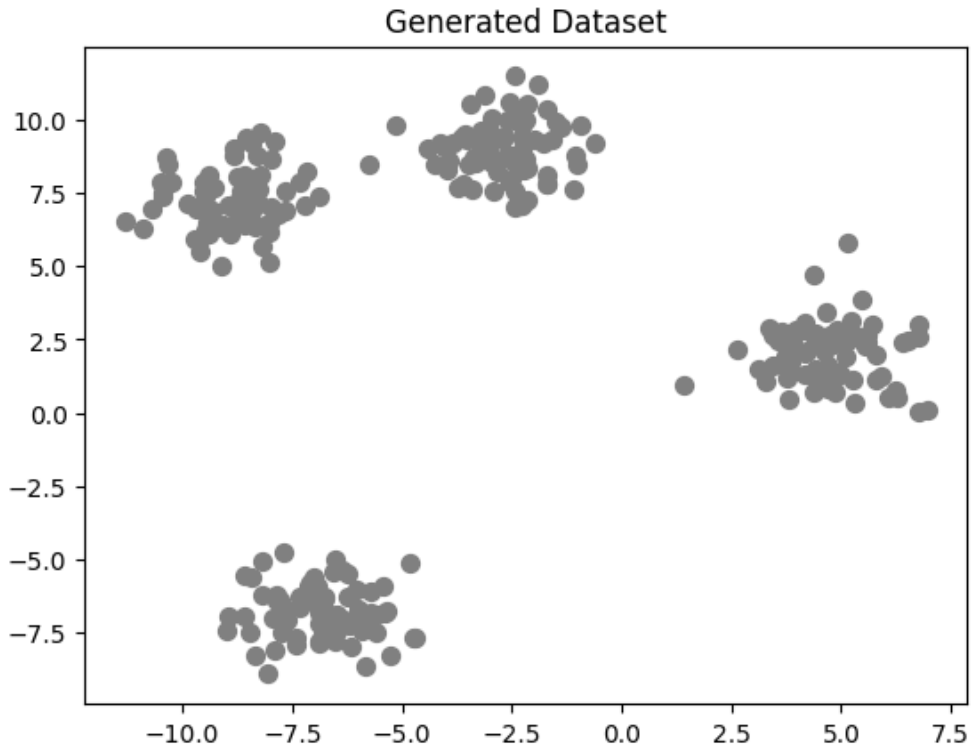
Name:	Harsh Shah	**Roll No.:**	21BCP359
Division:	6	**Batch:**	G11
Aim:	Implement Dimensionality reduction using Principal Component Analysis (PCA) method.		

Objective

The objective of this lab assignment is to implement dimensionality reduction using Principal Component Analysis (PCA) and gain hands-on experience in reducing the dimensionality of a dataset while preserving its essential information.

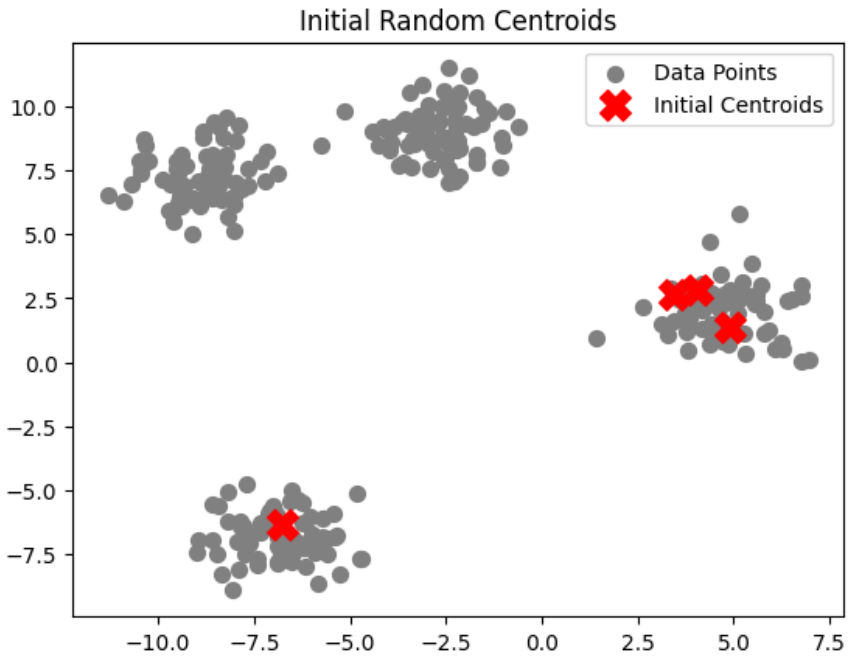
Code

```
import numpy as np

import matplotlib.pyplot as plt

from sklearn.datasets import make_blobs

X, y = make_blobs(n_samples=300, centers=4, random_state=42, cluster_std=1.0)

plt.scatter(X[:, 0], X[:, 1], s=50, c='gray')

plt.title('Generated Dataset')

plt.show()
```

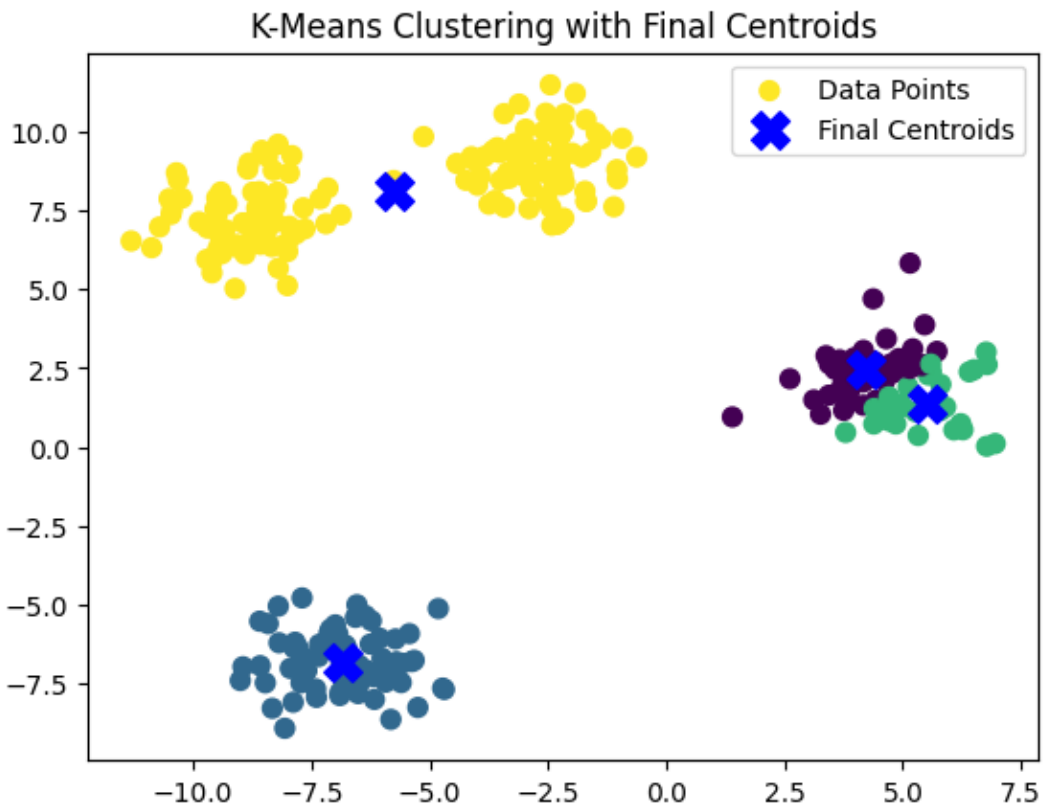


```
class KMeans:
    def __init__(self, k, max_iters=100):
        self.k = k
        self.max_iters = max_iters
        self.centroids = None

    def initialize_centroids(self, X):
        np.random.seed(42)
        random_indices = np.random.permutation(X.shape[0])
        centroids = X[random_indices[:self.k]]
        return centroids

    def assign_clusters(self, X, centroids):
        distances = np.linalg.norm(X[:, np.newaxis] - centroids, axis=2)
        return np.argmin(distances, axis=1)

    def update_centroids(self, X, labels):
        new_centroids = np.array([X[labels == i].mean(axis=0) for i in range(self.k)])
        return new_centroids

    def fit(self, X):
        self.centroids = self.initialize_centroids(X)

        for i in range(self.max_iters):
            labels = self.assign_clusters(X, self.centroids)
            new_centroids = self.update_centroids(X, labels)

            if np.all(self.centroids == new_centroids):
                break
            self.centroids = new_centroids

        return self.centroids, labels
```

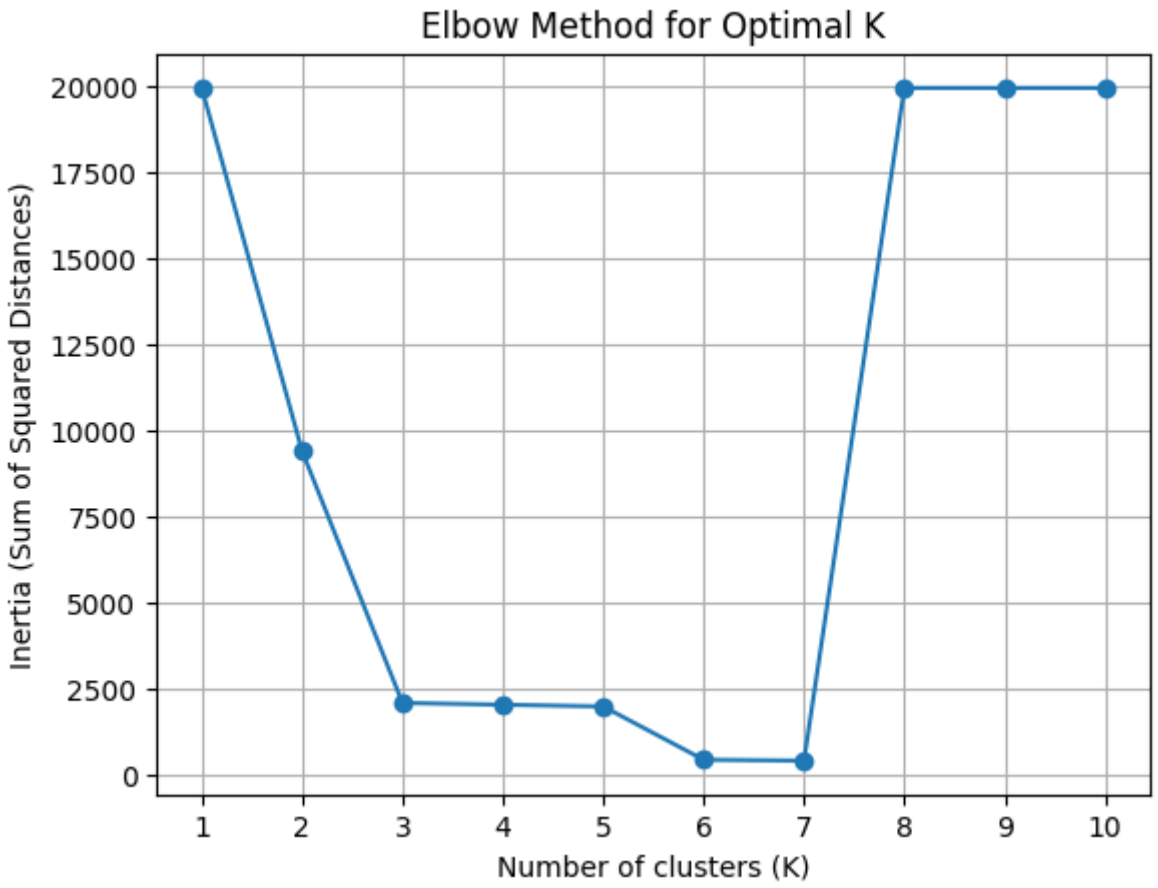
```
    def inertia(self, X, labels):
        return np.sum((X - self.centroids[labels]) ** 2)
kmeans = KMeans(k=4)
initial_centroids = kmeans.initialize_centroids(X)
centroids, labels = kmeans.fit(X)
plt.scatter(X[:, 0], X[:, 1], s=50, c='gray', label='Data Points')
plt.scatter(initial_centroids[:, 0], initial_centroids[:, 1], s=200, c='red', marker='X', label='Initial Centroids')
plt.title('Initial Random Centroids')
plt.legend()
plt.show()
```




```
plt.scatter(X[:, 0], X[:, 1], c=labels, s=50, cmap='viridis', label='Data Points')
plt.scatter(centroids[:, 0], centroids[:, 1], s=200, c='blue', marker='X', label='Final Centroids')
plt.title('K-Means Clustering with Final Centroids')
plt.legend()
plt.show()
```




```
inertia_values = []
K_values = range(1, 11)

for k in K_values:
    kmeans = KMeans(k=k)
    centroids, labels = kmeans.fit(X)
    inertia = kmeans.inertia(X, labels)
    inertia_values.append(inertia)
plt.plot(K_values, inertia_values, marker='o')
plt.title('Elbow Method for Optimal K')
plt.xlabel('Number of clusters (K)')
plt.ylabel('Inertia (Sum of Squared Distances)')
plt.xticks(K_values)
plt.grid()
plt.show()
```

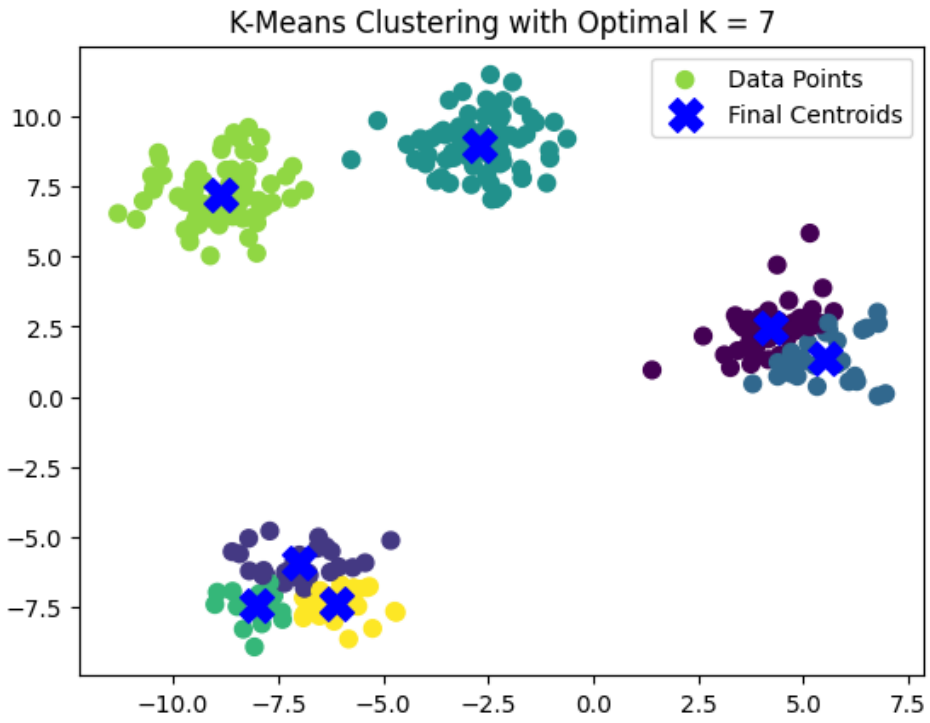



```
for k, inertia in zip(K_values, inertia_values):
    print(f"K = {k}, Inertia = {inertia:.2f}")
optimal_k = K_values[np.argmin(inertia_values)]
print(f"The optimal K is: {optimal_k}")
kmeans_optimal = KMeans(k=optimal_k)
centroids_optimal, labels_optimal = kmeans_optimal.fit(X)
plt.scatter(X[:, 0], X[:, 1], c=labels_optimal, s=50, cmap='viridis', label='Data Points')
plt.scatter(centroids_optimal[:, 0], centroids_optimal[:, 1], s=200, c='blue', marker='X', label='Final Centroids')
plt.title(f'K-Means Clustering with Optimal K = {optimal_k}')
plt.legend()
plt.show()
```

Output

```
K = 1, Inertia = 19953.77
K = 2, Inertia = 9416.21
K = 3, Inertia = 2110.41
K = 4, Inertia = 2058.54
K = 5, Inertia = 2007.60
K = 6, Inertia = 461.71
K = 7, Inertia = 434.73
K = 8, Inertia = 19953.77
K = 9, Inertia = 19953.77
K = 10, Inertia = 19953.77
```

```
The optimal K is: 7
```



A Project Report

on

s

FP Growth Algorithm

by

Harsh Shah

21BCP359

Under the Guidance of

Dr. Archana Nigam

Assistant Professor

For the Course

Mahine Learning Lab

20CP401P

Submitted to

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INDEX

PROBLEM STATEMENT

Mining frequent patterns in transaction databases, time-series databases, and many other kinds of databases has been studied popularly in data mining research. Most of the previous studies adopt an Apriori-like candidate set generation-and-test approach. However, candidate set generation is still costly, especially when there exist prolific patterns and/or long patterns.

In this project I have implemented a novel frequent pattern tree (FP-tree) structure, which is an extended prefix-tree structure for storing compressed, crucial information about frequent patterns, and develop an efficient FP-tree-based mining method, FP-growth, for mining the complete set of frequent patterns by pattern fragment growth.

INTRODUCTION

The **Frequent Pattern Growth (FP-Growth) algorithm** is a widely used technique for mining frequent item-sets in a transaction dataset. The FP-Growth Algorithm proposed by ***Han in***. This is an efficient and scalable method for mining the complete set of frequent patterns by pattern fragment growth, using an extended prefix-tree structure for storing compressed and crucial information about frequent patterns named frequent-pattern tree (FP-tree).

The algorithm is primarily used for association rule learning and market basket analysis to uncover relationships between items in transactional data. It identifies item-sets that occur together frequently, which is useful in areas like retail, e-commerce, and recommendation systems. Unlike the Apriori algorithm, which generates candidate sets and iteratively reduces them, FP-Growth uses a more efficient method that avoids candidate generation, making it faster and more scalable for large datasets.

DATASET DESCRIPTION

The dataset utilized for the project consists of a series of transactions, each recording the items purchased by customers. The data includes transactions, with various products represented by unique letters. This type of dataset, often referred to as "market basket data", captures customer purchasing behaviour and serves as the basis for discovering frequent item-sets and association rules.

Table 1: Input Data

TID	Items Bought
100	F-A-C-D-G-I-M-P
200	A-B-C-F-L-M-O
300	B-F-H-J-O
400	B-C-K-S-P
500	A-F-C-E-L-P-M-N

Below is a brief description and analysis of the dataset:

- The dataset shown in *Table 1* contains two main columns: **TID (Transaction ID)** and **Items Bought**.
- Each entry under "Items Bought" lists products purchased in a transaction, represented by uppercase letters, separated by hyphens (e.g., *"F-A-C-D-G-I-M-P"*).
- The dataset features a mix of commonly occurring items such as *A*, *B*, *C*, *F*, and *M*, as well as less frequent items such as *D*, *G*, and *S*.
- Certain products, such as *A*, *C*, and *F*, appear in multiple transactions, suggesting their popularity and potential frequent itemset status.

METHODOLOGY

1. **Construct the FP-Tree**:
    - **Scan the dataset** to calculate the frequency of each item.
    - **Filter out items** that do not meet the minimum support threshold.
    - **Sort items** in descending order of frequency to maintain consistency across transactions.
    - **Build the tree** by inserting transactions, ensuring that items follow the same order at each insertion. Nodes are created for each item, with links to parent nodes and links connecting identical items for traversal.
2. **Mine the FP-Tree**:
    - **Start from the least frequent item** in the header table and form conditional patterns based on paths leading to that item.
    - **Construct conditional FP-trees** for each item using its conditional pattern base (a sub-database of paths).
    - **Recursively mine** each conditional FP-tree to find frequent item-sets, adding them to the list of results.

From the FP-tree construction process, we can see that one needs exactly two scans of the transaction database, the first collects the set of frequent items, and the second constructs the FP-tree. The cost of inserting a transaction T into the FP-tree is $O(|T|)$, where $|T|$ is the number of frequent items in Transactions. We will show that the FP-tree contains the complete information for frequent pattern mining.

The FP-Tree structure in *Figure 1* allows for the compression of large datasets into a compact representation that still retains the necessary information for mining.

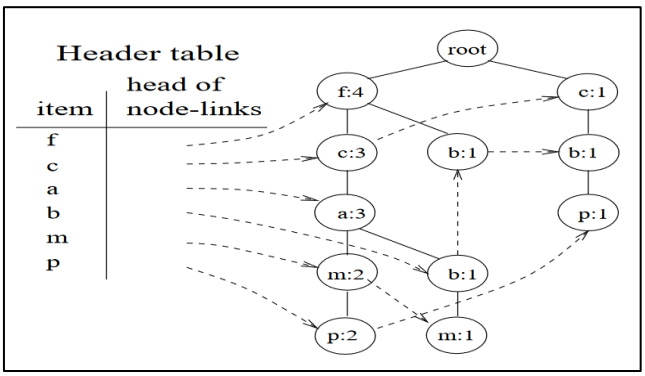

Figure 1: The FP Tree

RESULTS AND INSIGHTS

The dataset consisting of transactions with various products was analysed using the FP-Growth algorithm to mine frequent patterns. Below, we break down the results and provide an analysis of the key findings:

Frequency Map:

The first step involved scanning the dataset to calculate the frequency of each item. The frequency map generated from this scan was: {P: 3, A: 3, B: 3, C: 4, M: 3, F: 4}

This map indicates how many times each item appeared across all transactions. The minimum support threshold for pattern mining was set to 3 such that only items meeting or exceeding this threshold were retained.

Ordered Item Sets:

After filtering and sorting the items by their frequency, transactions were restructured into ordered item sets: [[P, A, C, F, M], [A, B, C, F, M], [B, F], [B, P, C], [P, A, C, F, M]]

Each transaction was sorted in descending order of item frequency, ensuring consistency and facilitating the construction of the FP-Tree. Items not meeting the minimum support threshold were omitted, which streamlined the dataset for more efficient mining.

Frequent Patterns:

The frequent patterns discovered, along with their respective support counts are shown in *Table 2*.

Table 2: Frequent Patterns Observed

{C, P}: 3	{M, F}: 3
{F, A}: 3	{F, C}: 4
{C, A}: 3	{C, A, M}: 3
{F, C, A}: 4	{F, A, M}: 3
{M, A}: 3	{F, C, M}: 3
{M, C}: 3	{F, C, A, M}: 3

The high frequency of item-sets like {F, C} and {A, F, C} highlights product combinations that are often purchased in tandem, suggesting potential product bundling opportunities for businesses. Additionally, the presence of item {M} in several frequent item-sets indicates it plays a significant role in purchasing patterns within the dataset.

CHALLENGES FACED

Implementing the FP-Growth algorithm presented several challenges, including data pre-processing and memory management. Ensuring consistent data formats, sorting items by frequency, and managing large data structures proved difficult. Handling memory efficiently during the tree construction and traversal phases was essential, especially when scaling to larger datasets, as it significantly impacted the system's performance.

Additionally, selecting an optimal minimum support threshold was challenging. A low threshold generated excessive patterns, making analysis complex, while a higher one risked omitting valuable insights. Interpreting the results to extract meaningful patterns required careful consideration and clear visualization strategies to present actionable findings, underscoring the balance needed between computational efficiency and interpretability.

CONCLUSION

The **FP-Growth algorithm** stands as a powerful and efficient solution for mining frequent item-sets from large datasets. By eliminating the need for candidate generation and employing a compact data structure in the form of an FP-tree, it significantly reduces the computational overhead compared to traditional methods like the Apriori algorithm. This makes FP-Growth particularly suitable for real-world applications where datasets are vast and require scalable solutions.

The algorithm's use in various domains—ranging from market basket analysis to web usage mining and bioinformatics—demonstrates its versatility and impact in uncovering hidden patterns that can inform decision-making and strategic initiatives. Despite its efficiency, careful consideration should be given to memory management when working with extensive or highly dense datasets, as the construction of the FP-tree may demand significant resources.

CODE

The program is divided into 4 modules (Java files): ***Main, FPGrowth, FPComponents, FileOps***.

Main.java - *Contains the Main Class which performs the algorithm step-by-step*

```
public class Main {
    public static void main(String[] args) {
        String fileName = "test";
        String inputFile = "data/" + fileName + ".csv";
        String outPutFile = "results/" + fileName + ".txt";
        int minSupport = 3;
        FPGrowth fpGrowth = new FPGrowth(minSupport);

        // Read transactions from CSV
        List<List<String>> transactions = FileOps.readCSV(inputFile);

        // 1. Create Frequency Map
        Map<String, Integer> sortedMap = new
HashMap<>(fpGrowth.createFrequencyMap(transactions));

        // 2. Create Ordered-Item Set
        List<List<String>> filteredTransactions = new
ArrayList<>(fpGrowth.createOrderedItemSet(sortedMap, transactions));

        // 3. Create Frequent Pattern Tree
        Map<String, Integer> frequentPatterns = fpGrowth.findFrequentPatterns(filteredTransactions);

        // Write results to file
        String output = "Transactions: \n" + transactions + "\n" +
                "\nFrequency Map: \n" + sortedMap + "\n" +
                "\nOrdered-Item Set: \n" + filteredTransactions + "\n" +
                "\nFrequent Patterns:\n" + fpGrowth.formatOutput(frequentPatterns);
        FileOps.writeToFile(output, outPutFile);
    }
}
```

FPGrowth.java - *Contains the logic for FPGrowth algorithm*

```
public class FPGrowth {
    private final int minSupport;
    private final Map<String, Integer> patternSupport;

    public FPGrowth(int minSupport) {
        this.minSupport = minSupport;
        this.patternSupport = new HashMap<>();
    }
}
```

```
public Map<String, Integer> createFrequencyMap(List<List<String>> transactions) {
    Map<String, Integer> itemFrequencies = new HashMap<>();
    for (List<String> transaction : transactions) {
        for (String item : transaction) {
            itemFrequencies.merge(item, 1, Integer::sum);
        }
    }

    itemFrequencies.entrySet().removeIf(entry -> entry.getValue() < minSupport);

    return itemFrequencies.entrySet().stream().sorted((entry1, entry2) ->
entry2.getValue().compareTo(entry1.getValue())).collect(Collectors.toMap(Map.Entry::getKey,
Map.Entry::getValue, (e1, e2) -> e1, LinkedHashMap::new));
}

public List<List<String>> createOrderedItemSet(Map<String, Integer> sortedMap, List<List<String>>
transactions) {
    Set<String> validItems = sortedMap.keySet();
    List<List<String>> filteredTransactions = new ArrayList<>();
    for (List<String> transaction : transactions) {
        Set<String> filteredTransactionSet = new HashSet<>();
        for (String item : transaction) {
            if (validItems.contains(item)) {
                filteredTransactionSet.add(item);
            }
        }
        filteredTransactions.add(new ArrayList<>(filteredTransactionSet));
    }
    return filteredTransactions;
}

public Map<String, Integer> findFrequentPatterns(List<List<String>> transactions) {
    FPTree tree = new FPTree(minSupport);
    tree.buildFPTree(transactions);

    minePatterns(tree, new ArrayList<>());
    return patternSupport;
}

public void minePatterns(FPTree tree, List<String> prefix) {
    if (tree.root.children.isEmpty()) {
        return;
    }

    for (Map.Entry<String, FPNode> entry : tree.headerTable.entrySet()) {
        String item = entry.getKey();
        List<String> newPattern = new ArrayList<>(prefix);
        newPattern.add(item);

        int support = 0;
```

```
        FPNode node = entry.getValue();
        while (node != null) {
            support += node.count;
            node = node.link;
        }
        if (support >= minSupport) {
            // Store pattern with its support count
            if (newPattern.size() > 1) { // Only store patterns with 2 or more items
                List<String> sortedPattern = new ArrayList<>(newPattern);
                String patternKey = String.join(",", sortedPattern);
                patternSupport.put(patternKey, support);
            }

            List<List<String>> conditionalPatternBase = new ArrayList<>();
            node = entry.getValue();

            while (node != null) {
                List<String> path = new ArrayList<>();
                FPNode current = node.parent;
                while (current.item != null) {
                    path.addFirst(current.item);
                    current = current.parent;
                }

                if (!path.isEmpty()) {
                    for (int i = 0; i < node.count; i++) {
                        conditionalPatternBase.add(new ArrayList<>(path));
                    }
                }
                node = node.link;
            }
            if (!conditionalPatternBase.isEmpty()) {
                FPTree conditionalTree = new FPTree(minSupport);
                conditionalTree.buildFPTree(conditionalPatternBase);
                minePatterns(conditionalTree, newPattern);
            }
        }
    }
}

public StringBuilder formatOutput(Map<String, Integer> frequentPatterns) {
    StringBuilder output = new StringBuilder();

    List<Map.Entry<String, Integer>> sortedPatterns = new ArrayList<>(frequentPatterns.entrySet());
    sortedPatterns.sort((e1, e2) -> {
        int supportCompare = e2.getValue().compareTo(e1.getValue());
        if (supportCompare != 0) return supportCompare;
        return e1.getKey().compareTo(e2.getKey());
    });
```

```
    for (Map.Entry<String, Integer> entry : sortedPatterns) {
        output.append(entry.getKey()).append(" = ").append(entry.getValue());
        output.append("\n");
    }
    return output;
}
```

FPComponents.java - *Contains **FPNode**, **FPTree** classes which are data structures for the FPTree*

```
class FPNode {
    String item;
    int count;
    FPNode parent;
    Map<String, FPNode> children;
    FPNode link;

    public FPNode(String item, int count) {
        this.item = item;
        this.count = count;
        this.children = new HashMap<>();
        this.link = null;
        this.parent = null;
    }

    public void increment(int count) {
        this.count += count;
    }
}

class FPTree {
    FPNode root;
    Map<String, FPNode> headerTable;
    int minSupport;

    public FPTree(int minSupport) {
        this.root = new FPNode(null, 0);
        this.headerTable = new HashMap<>();
        this.minSupport = minSupport;
    }

    public void buildFPTree(List<List<String>> transactions) {
        Map<String, Integer> itemFrequency = new HashMap<>();

        for (List<String> transaction : transactions) {
            for (String item : transaction) {
                itemFrequency.put(item, itemFrequency.getOrDefault(item, 0) + 1);
            }
```

```
        }

        itemFrequency.entrySet().removeIf(entry -> entry.getValue() < minSupport);

        for (List<String> transaction : transactions) {
            List<String> modifiableTransaction = new ArrayList<>(transaction);

            modifiableTransaction.sort((a, b) -> {
                int freqCompare = itemFrequency.getOrDefault(b,
0).compareTo(itemFrequency.getOrDefault(a, 0));
                return freqCompare != 0 ? freqCompare : a.compareTo(b);
            });

            modifiableTransaction.removeIf(item -> !itemFrequency.containsKey(item));

            insertTransaction(modifiableTransaction);
        }
    }

    private void insertTransaction(List<String> transaction) {
        FPNode current = root;
        for (String item : transaction) {
            current = insertNode(current, item);
        }
    }

    private FPNode insertNode(FPNode parent, String item) {
        FPNode node = parent.children.get(item);
        if (node == null) {
            node = new FPNode(item, 1);
            node.parent = parent;
            parent.children.put(item, node);

            if (!headerTable.containsKey(item)) {
                headerTable.put(item, node);
            } else {
                FPNode link = headerTable.get(item);
                while (link.link != null) {
                    link = link.link;
                }
                link.link = node;
            }
        } else {
            node.increment(1);
        }
        return node;
    }
}
```

FileOps.java - *Contains methods for reading CSV file and writing results into file.*

```
public class FileOps {
    public static List<List<String>> readCSV(String filePath) {
        List<List<String>> transactions = new ArrayList<>();
        String line;

        try (BufferedReader br = new BufferedReader(new FileReader(filePath))) {
            br.readLine(); // Skip header row
            while ((line = br.readLine()) != null) {
                String[] parts = line.split(",");
                if (parts.length == 2) {
                    List<String> productList = Arrays.asList(parts[1].split("-"));
                    transactions.add(productList);
                }
            }
        } catch (IOException e) {
            e.printStackTrace();
        }

        return transactions;
    }

    public static void writeToFile(String frequentPatterns, String filePath) {
        try (BufferedWriter writer = new BufferedWriter(new FileWriter(filePath))) {
            writer.write(frequentPatterns);

            System.out.println("Output written to " + filePath);
        } catch (IOException e) {
            e.printStackTrace();
        }
    }
}
```

OUTPUT

Figure 2 shows the output of the program. The output is stored in a text file for future use.

```
Transactions:
[[F, A, C, D, G, I, M, P], [A, B, C, F, L, M, O], [B, F, H, J, O], [B, C, K, S, P], [A, F, C, E, L, P, M, N]]

Frequency Map:
{P=3, A=3, B=3, C=4, M=3, F=4}

Ordered-Item Set:
[[P, A, C, F, M], [A, B, C, F, M], [B, F], [P, B, C], [P, A, C, F, M]]

Frequent Patterns:
A,C = 3
A,F = 3
A,F,C = 3
F,C = 3
M,A = 3
M,C = 3
M,C,A = 3
M,F = 3
M,F,A = 3
M,F,C = 3
M,F,C,A = 3
P,C = 3
```

Figure 2: Output of Algorithm