Task 2 Data Exploration with Python

a) Exploratory Data Analysis in Python

In [1]:
```python
import pandas as pd
import matplotlib.pyplot as plt

df = pd.read_csv("GHG_Data.csv")

# Overview of the dataset
print(df.head())
print(df.info())
print(df.describe())
```

```
   Year  Ontario GHG ID                          Facility Owner  \
0  2010            1001                   ADM Agri-Industries
1  2010            1002                 Air Products Canada Ltd
2  2010            1003  Algonquin Power Energy From Waste Inc.
3  2010            1005              ArcelorMittal Dofasco Inc.
4  2010            1006        Atlantic Packaging Products Ltd.

                         Facility Name Facility City  \
0                          ADM Windsor       Windsor
1             Corunna Hydrogen Facility       Corunna
2  Algonquin Power  Energy from Waste Inc.      Brampton
3                     Dofasco Hamilton      Hamilton
4                         111 Progress   Scarborough

   Facility Primary NAICS Code  \
0                       311224
1                       325120
2                       562210
3                       331110
```

b) Summary Statistics

In [15]:
```python
#import piplite
#await piplite.install('seaborn')
```

In [14]:
```
import seaborn as sns


# Display the first few rows of the dataset
print(df.head())

# Get the basic statistics of numerical columns
print(df.describe())

# Get information about the data types and missing values
print(df.info())
```

```
   Year  Ontario GHG ID                           Facility Owner  \
0  2010            1001                     ADM Agri-Industries
1  2010            1002                 Air Products Canada Ltd
2  2010            1003  Algonquin Power Energy From Waste Inc.
3  2010            1005               ArcelorMittal Dofasco Inc.
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                            Facility Name Facility City  \
0                            ADM Windsor       Windsor
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2  Algonquin Power  Energy from Waste Inc.      Brampton
3                        Dofasco Hamilton      Hamilton
4                            111 Progress   Scarborough

   Facility Primary NAICS Code  \
0                       311224
1                       325120
2                       562210
3                       331110
```
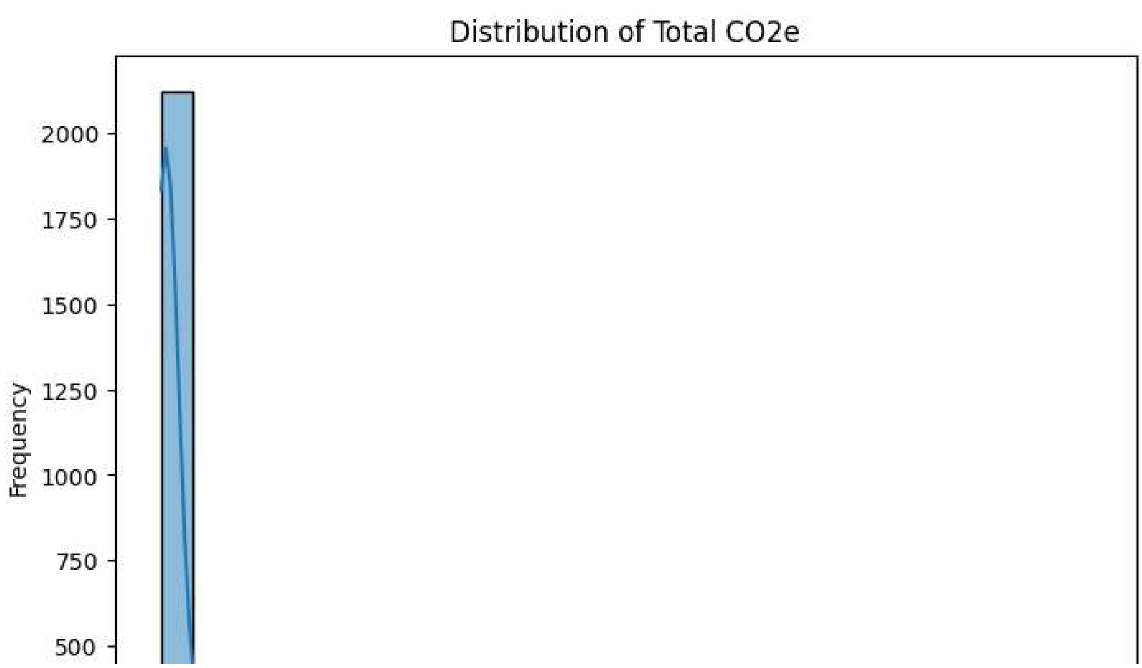

In [16]:
```python
# Plot a histogram for the "Total CO2e from all sources in CO2e (t)" column
plt.figure(figsize=(8, 6))
sns.histplot(df['Total CO2e from all sources in CO2e (t)'], bins=30, kde=True)
plt.xlabel('Total CO2e (t)')
plt.ylabel('Frequency')
plt.title('Distribution of Total CO2e')
plt.show()

# Scatter plot between "Carbon dioxide (CO2) from non-biomass in CO2e (t)" and
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Carbon dioxide (CO2) from non-biomass in CO2e (t)', y='Tota
plt.xlabel('CO2 from non-biomass (t)')
plt.ylabel('Total CO2e (t)')
plt.title('Scatter Plot of CO2 from non-biomass vs. Total CO2e')
plt.show()

# Box plot for the "Facility City" vs. "Total CO2e"
plt.figure(figsize=(10, 6))
sns.boxplot(x='Facility City', y='Total CO2e from all sources in CO2e (t)', da
plt.xticks(rotation=45, ha='right')
plt.xlabel('Facility City')
plt.ylabel('Total CO2e (t)')
plt.title('Box Plot of Total CO2e by Facility City')
plt.show()

# Correlation matrix
correlation_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```



Task 3 Data Preprocessing in Python

a) and b) Data Preprocessing

Handling Missing Values

In [22]:
```
# Check for missing values
print(df.isnull().sum())

# If you want to drop rows with any missing values
df.dropna(inplace=True)

# If you want to fill missing values with mean/median
# For example, filling missing values with mean for numerical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns
for col in numerical_cols:
    df[col].fillna(df[col].mean(), inplace=True)
```

```
Year                                                 0
Ontario GHG ID                                       0
Facility Owner                                       0
Facility Name                                        0
Facility City                                        0
Facility Primary NAICS Code                          0
Carbon dioxide (CO2) from non-biomass in CO2e (t)    0
Carbon dioxide (CO2) from biomass in CO2e (t)        0
Methane (CH4) in CO2e (t)                            0
Nitrous oxide (N2O) in CO2e (t)                      0
Sulphur hexafluoride (SF6) in CO2e (t)               0
Hydrofluorocarbons (HFCs) in CO2e (t)                0
Perfluorocarbons (PFCs) in CO2e (t)                  0
Nitrogen Trifluoride (NF3) in CO2e (t)               0
Total CO2e from all sources in CO2e (t)              0
Reporting Amount in CO2e (t)                         0
Verification Amount in CO2e (t)                      0
Accredited Verification Body                         0
dtype: int64
```

Handling Catogorical Data

In [18]:
```
# Perform one-hot encoding for categorical columns
categorical_cols = df.select_dtypes(include=['object']).columns
df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
```

Feature Scaling

In [19]:
```
from sklearn.preprocessing import MinMaxScaler

# Apply Min-Max scaling to numerical columns
scaler = MinMaxScaler()
df_encoded[numerical_cols] = scaler.fit_transform(df_encoded[numerical_cols])
```

Outlier Handling

In [20]:
```
# Outlier handling us
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df.loc[(df[column] < lower_bound) | (df[column] > upper_bound), column] = 

# Call the function for each numerical column
for col in numerical_cols:
    handle_outliers_iqr(col)
```

Data Splitting

In [21]:
```
from sklearn.model_selection import train_test_split

X = df_encoded.drop('Total CO2e from all sources in CO2e (t)', axis=1)
y = df_encoded['Total CO2e from all sources in CO2e (t)']

# Split the data into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, rando
```

Task 4 Implementing Missing Values

a) Two Machine learning Model

In [23]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Initialize the Random Forest Regressor
rf_model = RandomForestRegressor(random_state=42)

# Train the model
rf_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_rf = rf_model.predict(X_test)

# Evaluate the model
rmse_rf = mean_squared_error(y_test, y_pred_rf, squared=False)
r2_rf = r2_score(y_test, y_pred_rf)

print("Random Forest Model:")
print("Root Mean Squared Error (RMSE):", rmse_rf)
print("R-squared (R2) Score:", r2_rf)
```

```
Random Forest Model:
Root Mean Squared Error (RMSE): 0.005290408191517 16
R-squared (R2) Score: 0.9979629664088066
```

In [24]:

```python
from sklearn.svm import SVR

# Initialize the Support Vector Regressor
svm_model = SVR(kernel='linear')

# Train the model
svm_model.fit(X_train, y_train)

# Make predictions on the test set
y_pred_svm = svm_model.predict(X_test)

# Evaluate the model
rmse_svm = mean_squared_error(y_test, y_pred_svm, squared=False)
r2_svm = r2_score(y_test, y_pred_svm)

print("\nSupport Vector Machine Model:")
print("Root Mean Squared Error (RMSE):", rmse_svm)
print("R-squared (R2) Score:", r2_svm)
```

```
Support Vector Machine Model:
Root Mean Squared Error (RMSE): 0.08977304389489155
R-squared (R2) Score: 0.413440965899481
```

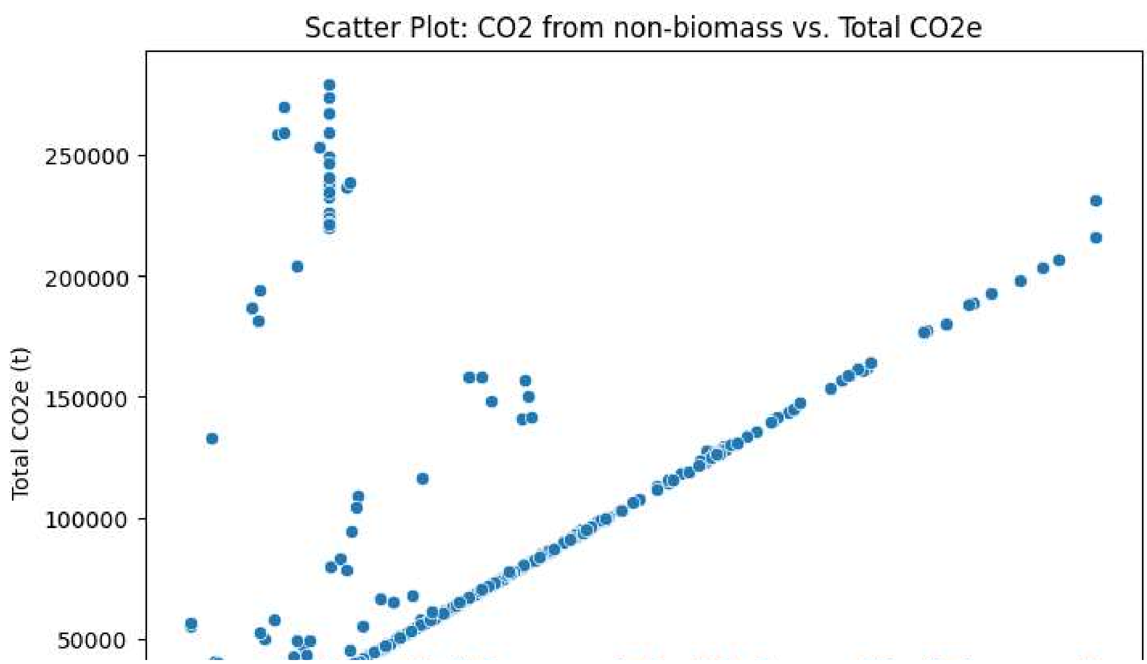
b) Evaluate and Compare

In [25]:
```
from sklearn.metrics import mean_squared_error, r2_score

# Evaluate Random Forest Model
y_pred_rf = rf_model.predict(X_test)
rmse_rf = mean_squared_error(y_test, y_pred_rf, squared=False)
r2_rf = r2_score(y_test, y_pred_rf)

# Evaluate Support Vector Machine (SVM) Model
y_pred_svm = svm_model.predict(X_test)
rmse_svm = mean_squared_error(y_test, y_pred_svm, squared=False)
r2_svm = r2_score(y_test, y_pred_svm)

# Display results
print("Random Forest Model:")
print("Root Mean Squared Error (RMSE):", rmse_rf)
print("R-squared (R2) Score:", r2_rf)

print("\nSupport Vector Machine Model:")
print("Root Mean Squared Error (RMSE):", rmse_svm)
print("R-squared (R2) Score:", r2_svm)
```

```
Random Forest Model:
Root Mean Squared Error (RMSE): 0.005290408191517 16
R-squared (R2) Score: 0.9979629664088066

Support Vector Machine Model:
Root Mean Squared Error (RMSE): 0.08977304389489155
R-squared (R2) Score: 0.413440965899481
```

In [26]:

```
# Scatter plot: CO2 from non-biomass vs. Total CO2e
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Carbon dioxide (CO2) from non-biomass in CO2e (t)', y='Total
plt.xlabel('CO2 from non-biomass (t)')
plt.ylabel('Total CO2e (t)')
plt.title('Scatter Plot: CO2 from non-biomass vs. Total CO2e')
plt.show()

# Heatmap: Correlation matrix
correlation_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()

# Bar chart: Facility City vs. Total CO2e
plt.figure(figsize=(12, 6))
sns.barplot(x='Facility City', y='Total CO2e from all sources in CO2e (t)', da
plt.xticks(rotation=45, ha='right')
plt.xlabel('Facility City')
plt.ylabel('Total CO2e (t)')
plt.title('Bar Chart: Facility City vs. Total CO2e')
plt.show()
```



In [29]:

```
import piplite
await piplite.install('plotly')
```

In [30]:

```
import plotly.express as px

# 1. Scatter plot: CO2 from non-biomass vs. Total CO2e (with Seaborn)
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Carbon dioxide (CO2) from non-biomass in CO2e (t)', y='Tota
plt.xlabel('CO2 from non-biomass (t)')
plt.ylabel('Total CO2e (t)')
plt.title('Scatter Plot: CO2 from non-biomass vs. Total CO2e')
plt.show()

# 2. Heatmap: Correlation matrix (with Seaborn)
correlation_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()

# 3. Bar chart: Facility City vs. Total CO2e (with Seaborn)
plt.figure(figsize=(12, 6))
sns.barplot(x='Facility City', y='Total CO2e from all sources in CO2e (t)', da
plt.xticks(rotation=45, ha='right')
plt.xlabel('Facility City')
plt.ylabel('Total CO2e (t)')
plt.title('Bar Chart: Facility City vs. Total CO2e')
plt.show()

# 4. Interactive bar chart: Facility City vs. Total CO2e (with Plotly)
fig = px.bar(df, x='Facility City', y='Total CO2e from all sources in CO2e (t)
fig.update_layout(xaxis_title='Facility City', yaxis_title='Total CO2e (t)')
fig.show()

# 5. Line chart: Year vs. Total CO2e (with Plotly)
fig = px.line(df, x='Year', y='Total CO2e from all sources in CO2e (t)', title
fig.update_layout(xaxis_title='Year', yaxis_title='Total CO2e (t)')
fig.show()
```