Team Enterpernures

Exploratory Data Analysis (CO_2 Emissions from Different Countries)

Data Source: Waste Disposal

Introduction

In recent years climate change & global warming has gained significant momentum. The one key sources of CO_2 emissions has been from countries. In this project the CO_2 emissions from all over countries will be investigated.

About the Dataset:

- Provided by the HP Z-Unlocked Challenge, the dataset used in this EDA has records covering approx. 30 years from 1990 to 2020. It holds a breakdown of CO_2 emissions for a number of countries . As it will become apparent, CO_2 emissions from country to country is increasing day by day and it is in inclined plan form.

Methodolgy:

- First of all whole data was explored. Redundent Data was removed to simplify the analysis. There were no missing values however distribution of data is not evenly distributed due to multiple reasons i.e CO_2 emission fluctuate in differents countries over years and years and different parts of the globe.
- We Divide our EDA into two parts.
  - Part 1 is EDA on whole data
  - Part 2 is EDA on Subcontinent Countries only

Part-1: EDA on Whole DataSet

Step-1: Importing Libraries

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

Step-2: Importing Dataset

```
df = pd.read_csv('waste_disposal_data_11-29-2021.csv')
df.head()
```

> **Output :**

Domain Code Domain Area Code (ISO3) Area Element Code Element Item Code Item Year Code Year Unit Value Flag Flag Description 0 GW Waste Disposal AFG Afghanistan 7273 Emissions (CO2) 6990 Incineration 1990 1990 kilotonnes 0.0 Fc Calculated data 1 GW Waste Disposal AFG Afghanistan 7273 Emissions (CO2) 6990 Incineration 1991 1991 kilotonnes 0.0 Fc Calculated data 2 GW Waste Disposal AFG Afghanistan 7273 Emissions (CO2) 6990 Incineration 1992 1992 kilotonnes 0.0 Fc Calculated data 3 GW Waste Disposal AFG Afghanistan 7273 Emissions (CO2) 6990 Incineration 1993 1993 kilotonnes 0.0 Fc Calculated data 4 GW Waste Disposal AFG Afghanistan 7273 Emissions (CO2) 6990 Incineration 1994 1994 kilotonnes 0.0 Fc Calculated data

Step-3: Data Shape

> Shape function tells us number of Observations and columns. In this dataset we have 14 columns and 46131 records or obervations

```
row, col=df.shape
print('Total number of observations/rows/entries:', row)
print('Total number of columns:', col)
```

> **Output :**

```
Number of Rows      =  6238
Number of Columns   =  14
```

Step-4: Data Structure

> Extracting Basic Dataset Information:
>
> - Our dataset contain
>   - RangeIndex: 0 - to - 6238
>   - Total Columns: 14
>   - No of Non-Null Values: Zero
>   - Dtypes: float64(1), int64(4), object(9)
>   - memory usage: 682.4+ KB

```
df.info()
```

> **Output :**

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6238 entries, 0 to 6237
Data columns (total 14 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Domain Code       6238 non-null   object
```

```
 1   Domain             6238 non-null   object
 2   Area Code (ISO3)   6238 non-null   object
 3   Area               6238 non-null   object
 4   Element Code       6238 non-null   int64
 5   Element            6238 non-null   object
 6   Item Code          6238 non-null   int64
 7   Item               6238 non-null   object
 8   Year Code          6238 non-null   int64
 9   Year               6238 non-null   int64
 10  Unit               6238 non-null   object
 11  Value              6238 non-null   float64
 12  Flag               6238 non-null   object
 13  Flag Description   6238 non-null   object
dtypes: float64(1), int64(4), object(9)
memory usage: 682.4+ KB
```

Step-5: Finding Missing Values

> DataSet is cleaned as far as missing values are concerned

```
df.isnull().sum()
```

> **Output :**

```
Domain Code         0
Domain              0
Area Code (ISO3)    0
Area                0
Element Code        0
Element             0
Item Code           0
Item                0
Year Code           0
Year                0
Unit                0
Value               0
Flag                0
Flag Description    0
dtype: int64
```

> DataSet is cleaned as far as missing values are concerned in percentage

```
df.isnull().sum() / df.shape[0] * 100
```

> **Output :**

```
Domain Code          0.0
Domain               0.0
Area Code (ISO3)     0.0
Area                 0.0
Element Code         0.0
Element              0.0
Item Code            0.0
Item                 0.0
Year Code            0.0
Year                 0.0
Unit                 0.0
Value                0.0
Flag                 0.0
Flag Description     0.0
dtype: float64
```

Step-6: Summary Statistics

```
df.describe()
```

> **Output :**

Element Code Item Code Year Code Year Value count 6238.0 6238.0 6238.000000 6238.000000 6238.000000 mean 7273.0 6990.0 2004.677300 2004.677300 202.675467 std 0.0 0.0 8.603289 8.603289 1066.676986 min 7273.0 6990.0 1990.000000 1990.000000 0.000000 25% 7273.0 6990.0 1997.000000 1997.000000 0.000000 50% 7273.0 6990.0 2005.000000 2005.000000 0.652579 75% 7273.0 6990.0 2012.000000 2012.000000 30.517272 max 7273.0 6990.0 2019.000000 2019.000000 11151.696408

Step-7: Value Counts

```
df.Value.value_counts()
```

> **Output :**

```
0.000000     2828
17.356301       1
17.343147       1
17.324444       1
17.311169       1
             ...
47.010034       1
47.179100       1
47.292824       1
46.997779       1
35.841750       1
```

```
Name: Value, Length: 3411, dtype: int64

```python
# unique values in each column
df.nunique
> **Output :**

```python
Domain Code              1
Domain                   1
Area Code (ISO3)       217
Area                   217
Element Code             1
Element                  1
Item Code                1
Item                     1
Year Code               30
Year                    30
Unit                     1
Value                 3411
Flag                     2
Flag Description         2
dtype: int64
```

Step-8: Feature Selection

1. Domain Code having GW Global Warming value only
2. Domain having Waste disposal value only
3. Area Code (ISO3) codes of different countries
4. Area representing different countries
5. Element Code representing code of CO2 as seven thousand two hundred seventy-three (7273)
6. Element having only one value as Emissions (CO2)
7. Item Code representing items codes that are only one
8. Item representing Incineration means the destruction of something in progress
9. Year Code representing different years codes
10. Year representing different years
11. Unit representing only one value kilotons
12. Value representing the number of CO2 emissions in unit kilotons
13. Flag representing flag short name that is only two
14. Flag Description represents two types of description over the flag

Clean data - exclude unnecessary data improved readability

```
df.drop(['Domain Code', 'Domain', 'Element Code', 'Element', 'Item Code', 'Item',
'Unit','Flag','Flag Description'], axis=1, inplace=True)
```

Label encoding to get a clear picture of data

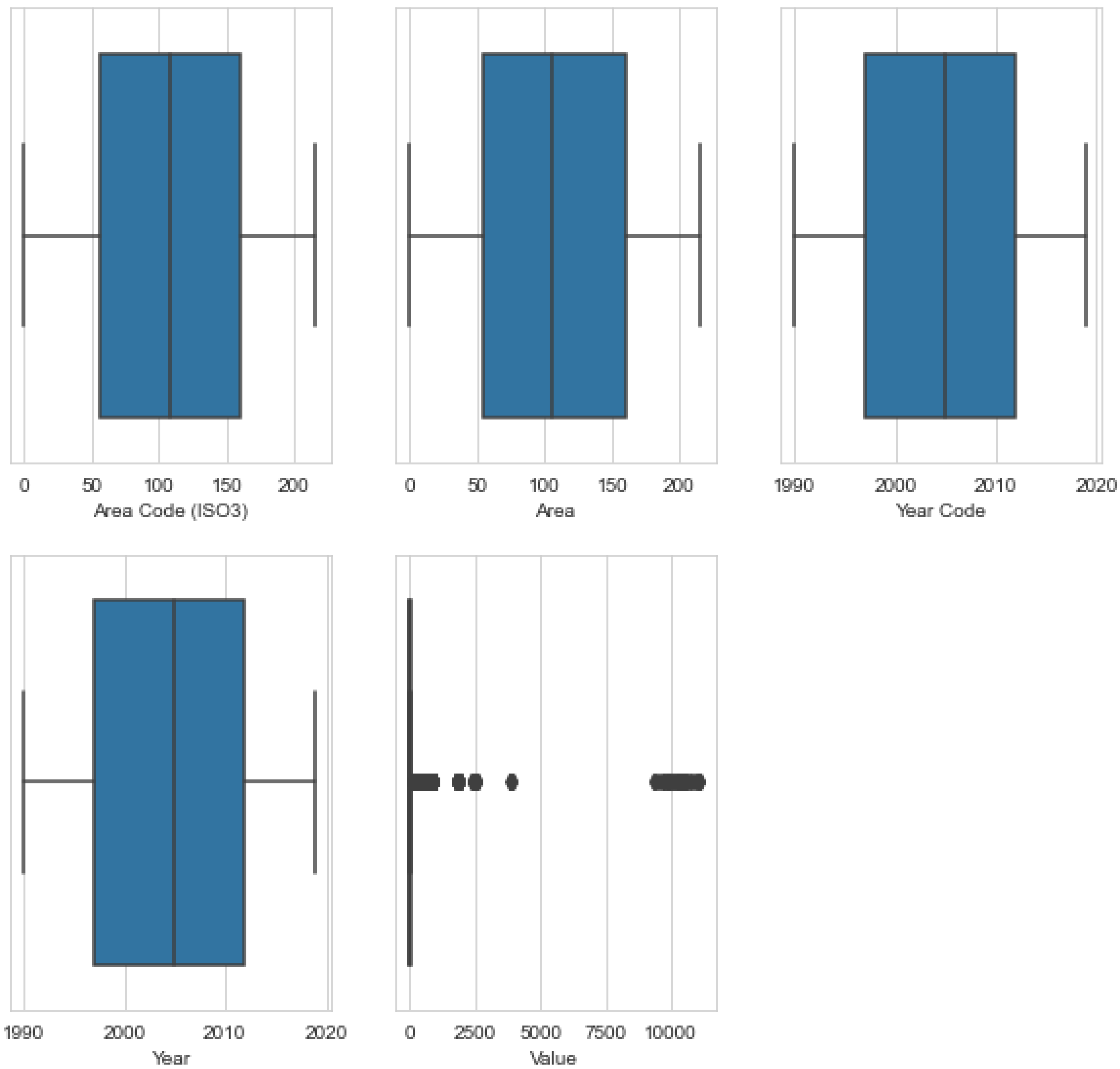
There are some columns which are not in use but to get a really clear picture lets use those as well.

```
from sklearn.preprocessing import LabelEncoder
label = LabelEncoder()
df['Domain'] = label.fit_transform(df['Domain'])
df['Domain Code'] = label.fit_transform(df['Domain Code'])
df['Area Code (ISO3)'] = label.fit_transform(df['Area Code (ISO3)'])
df['Area'] = label.fit_transform(df['Area'])
df['Element'] = label.fit_transform(df['Element'])
df['Item'] = label.fit_transform(df['Item'])
df['Unit'] = label.fit_transform(df['Unit'])
df['Flag'] = label.fit_transform(df['Flag'])
df['Flag Description'] = label.fit_transform(df['Flag Description'])
```

Step-9: Distribution of Data

> The data is extremely broadly distributed with many values in the range of 0 to 8.415818 with a strong skew to the right and kurtosis as 0 to 75.170198.

Before removing outliers

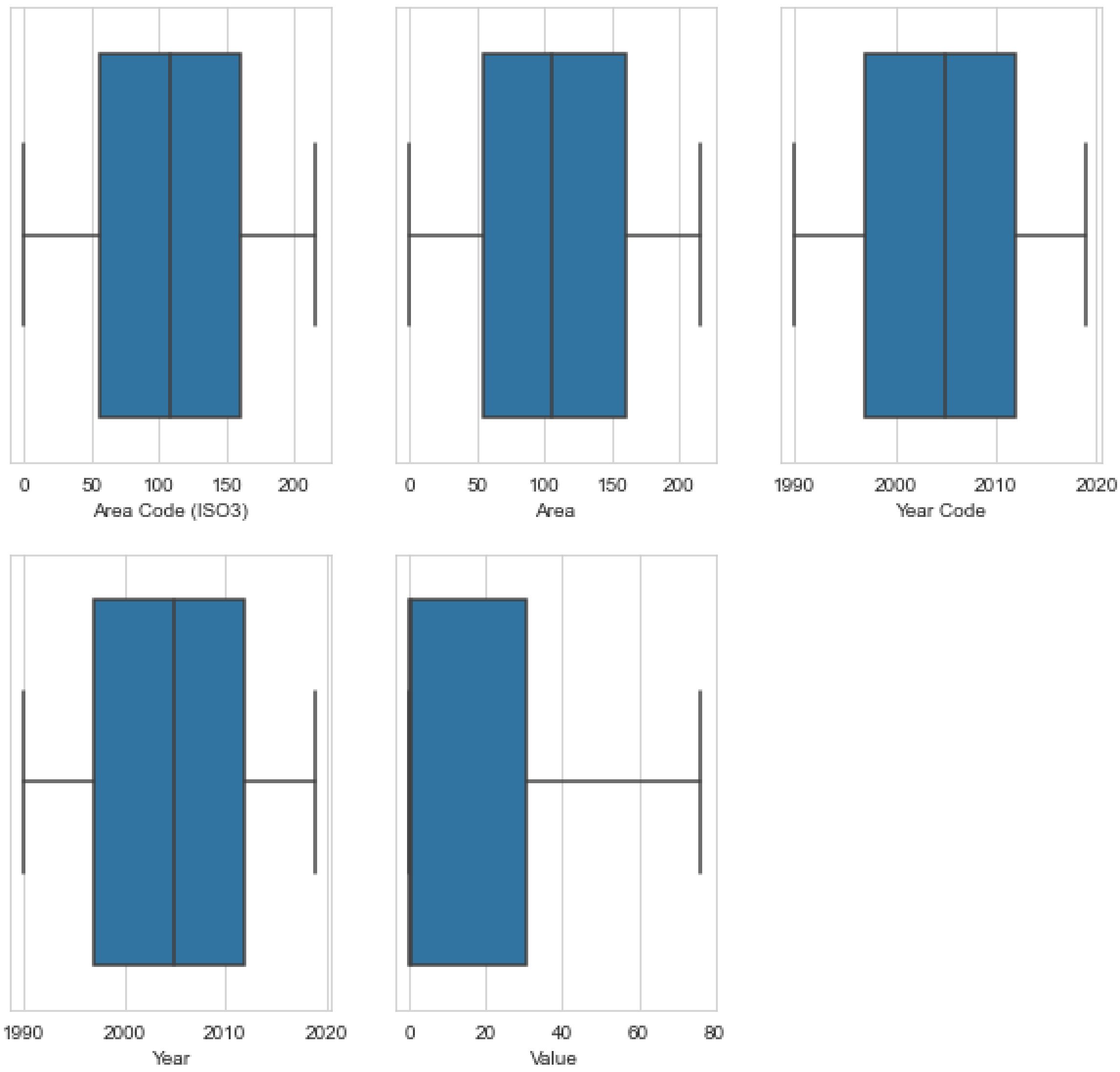


After removing outliers

With Interquartile range technique

there are some outliers so we are going to taking those off from data set

```
def mod_outlier(df):
    col_vals = df.columns
    df1 = df.copy()
    df = df._get_numeric_data()

    q1 = df.quantile(0.25)
    q3 = df.quantile(0.75)

    iqr = q3 - q1

    lower_bound = q1 - (1.5 * iqr)
    upper_bound = q3 + (1.5 * iqr)
    for col in col_vals:
        for i in range(0, len(df[col])):
            if df[col][i] < lower_bound[col]:
                df[col][i] = lower_bound[col]

            if df[col][i] > upper_bound[col]:
                df[col][i] = upper_bound[col]

    for col in col_vals:
        df1[col] = df[col]

        return(df1)
```

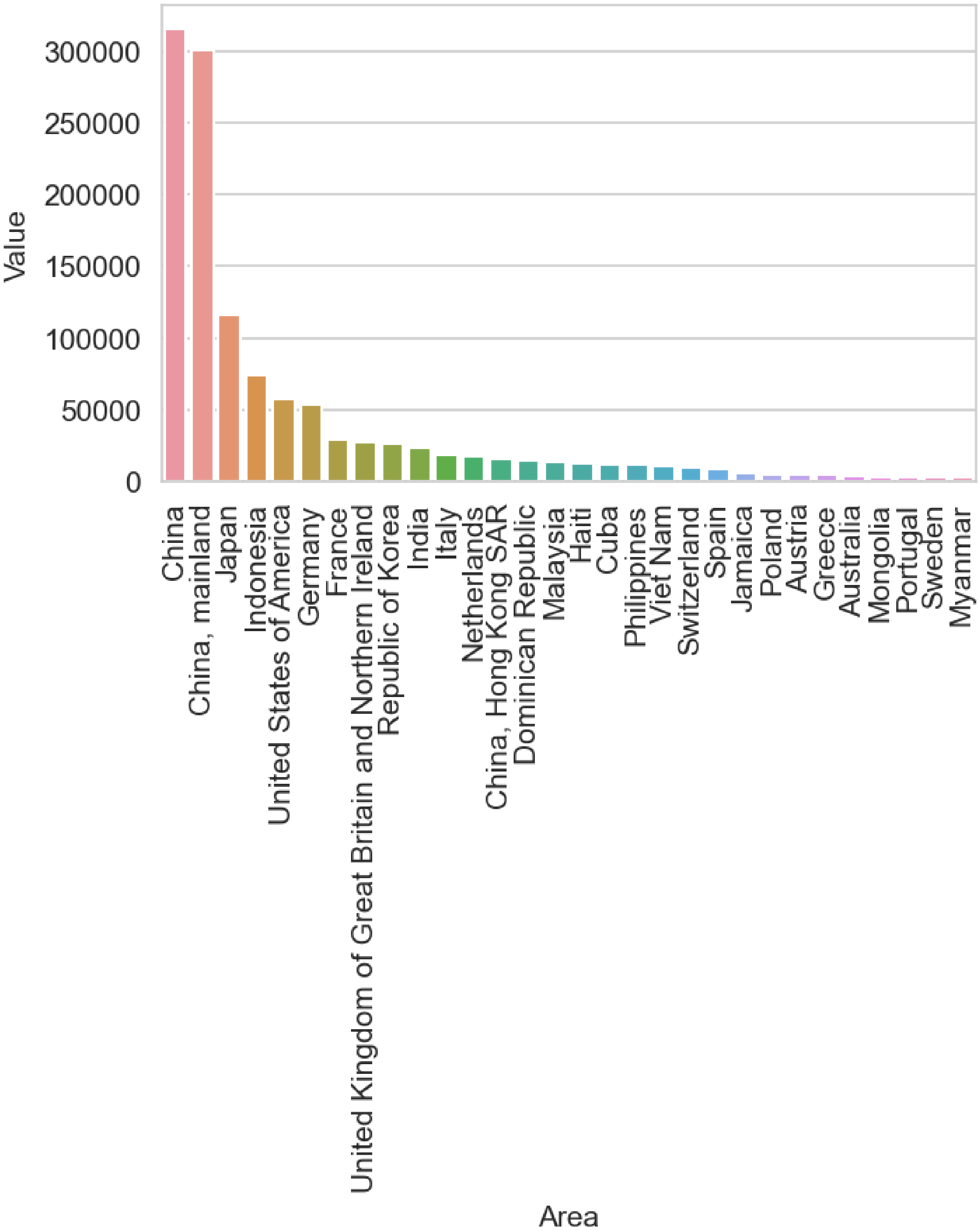


Step-9: Visualization of Data

Visualization of CO2 emissions over the years

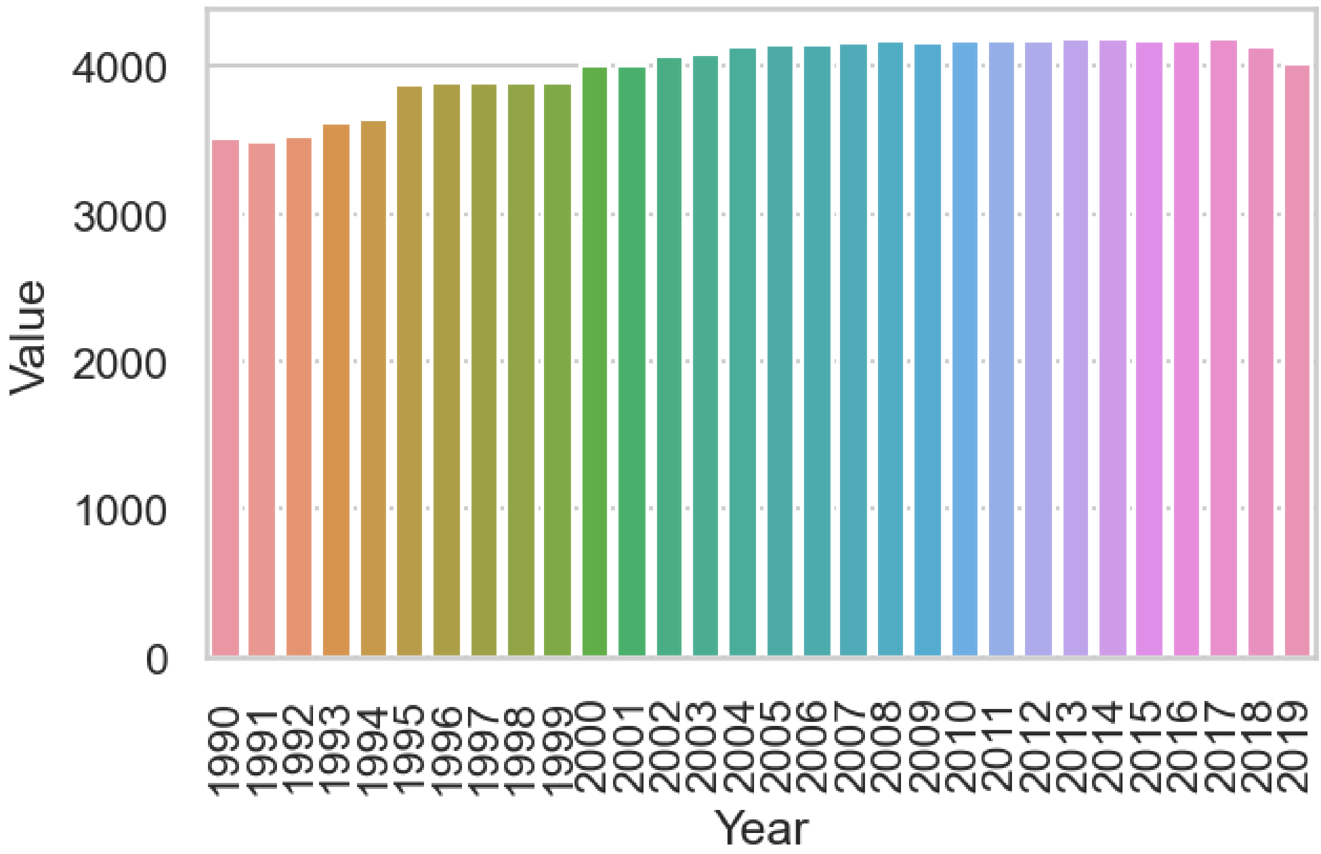
Before label encoding and outlier removal

```
# Data Distribution by top 30 countries
a = df.groupby(["Area"]).sum().sort_values(
    by=["Value"], ascending=False).head(30)
a
plt.figure(figsize=(5, 3), dpi=150, linewidth=2)
sns.barplot(x=a.index, y='Value', data=a)
plt.xticks(rotation=90)
```



Boxplot of CO2 emissions

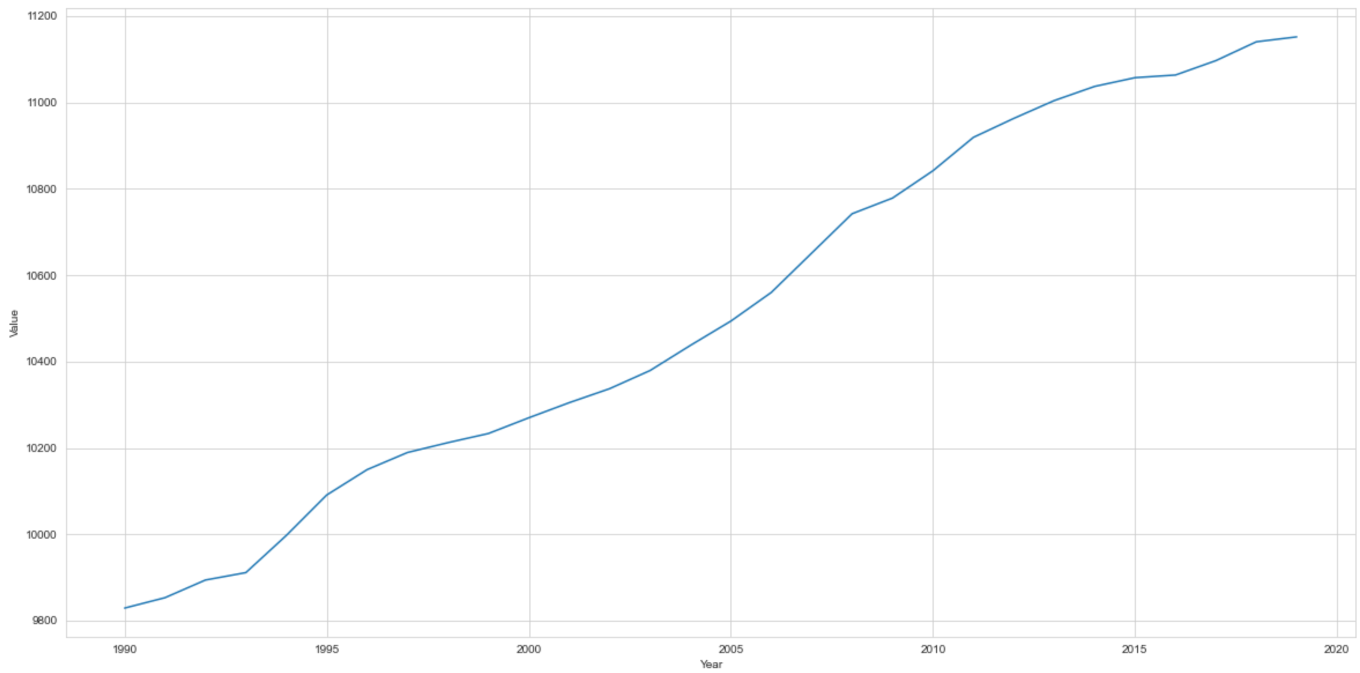
```
plt.figure(figsize=(5, 3), dpi=150, linewidth=2)
sns.barplot(x=s.index, y='Value', data=s)
plt.xticks(rotation=90)
plt.show()
```



Top 3 countries Emissioning with graphs

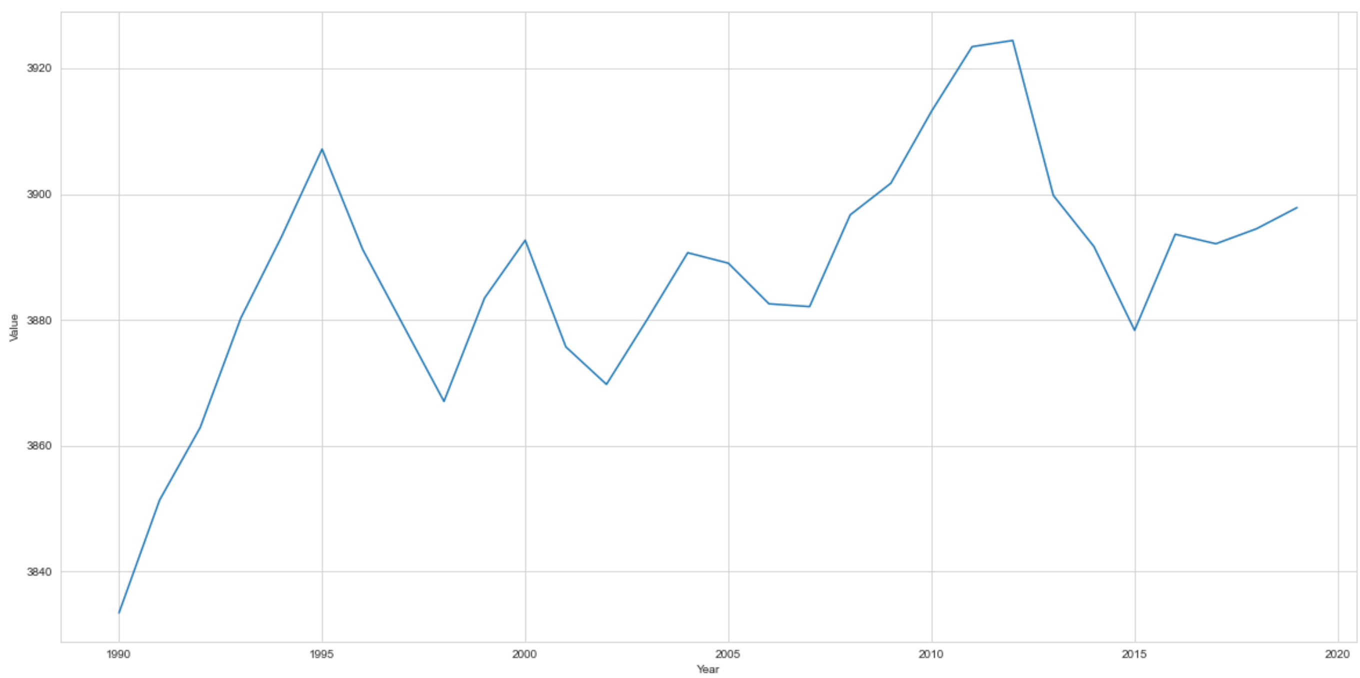
Ratio of CO2 over different years by China

```
plt.figure(figsize = (20,10))
sns.lineplot(x = "Year", y = "Value", data = df[df["Area"]=="China"])
plt.show()
```



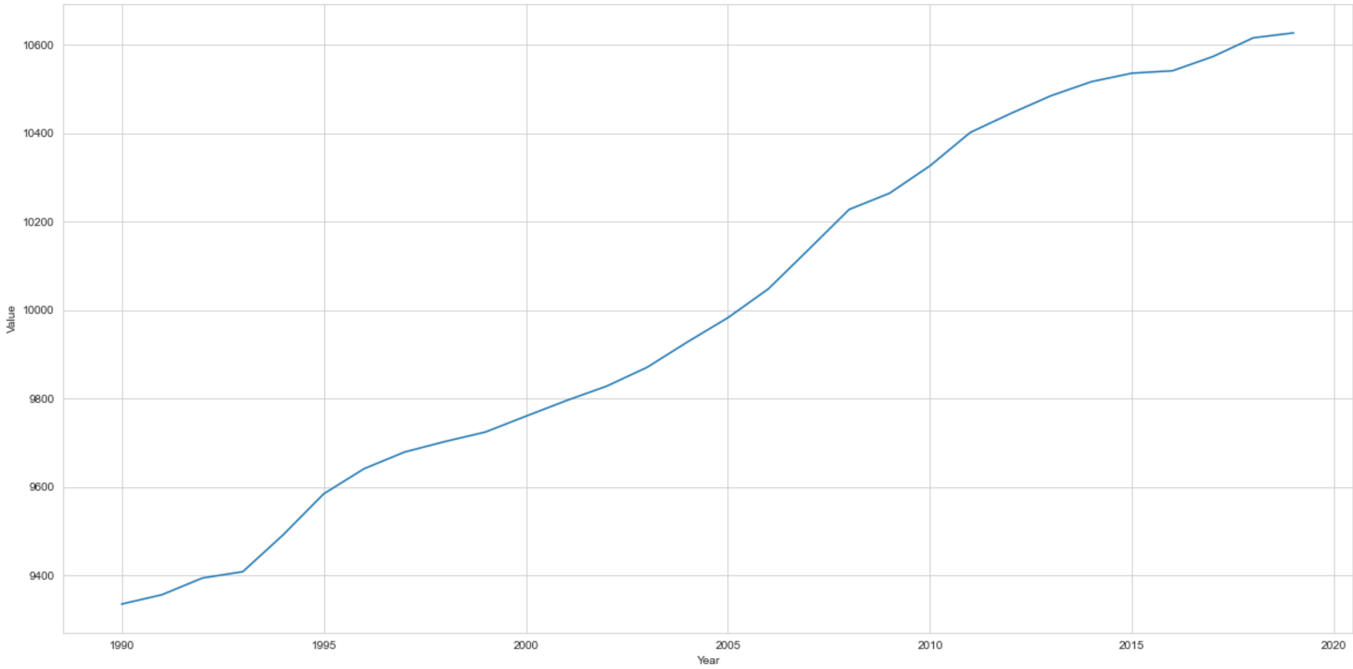
Ratio of CO2 over different years by Japan

```
plt.figure(figsize=(20, 10))
sns.lineplot(x="Year", y="Value", data=df[df["Area"] == "Japan"])
plt.show()
```



Ratio of CO2 over different years by China, mainland

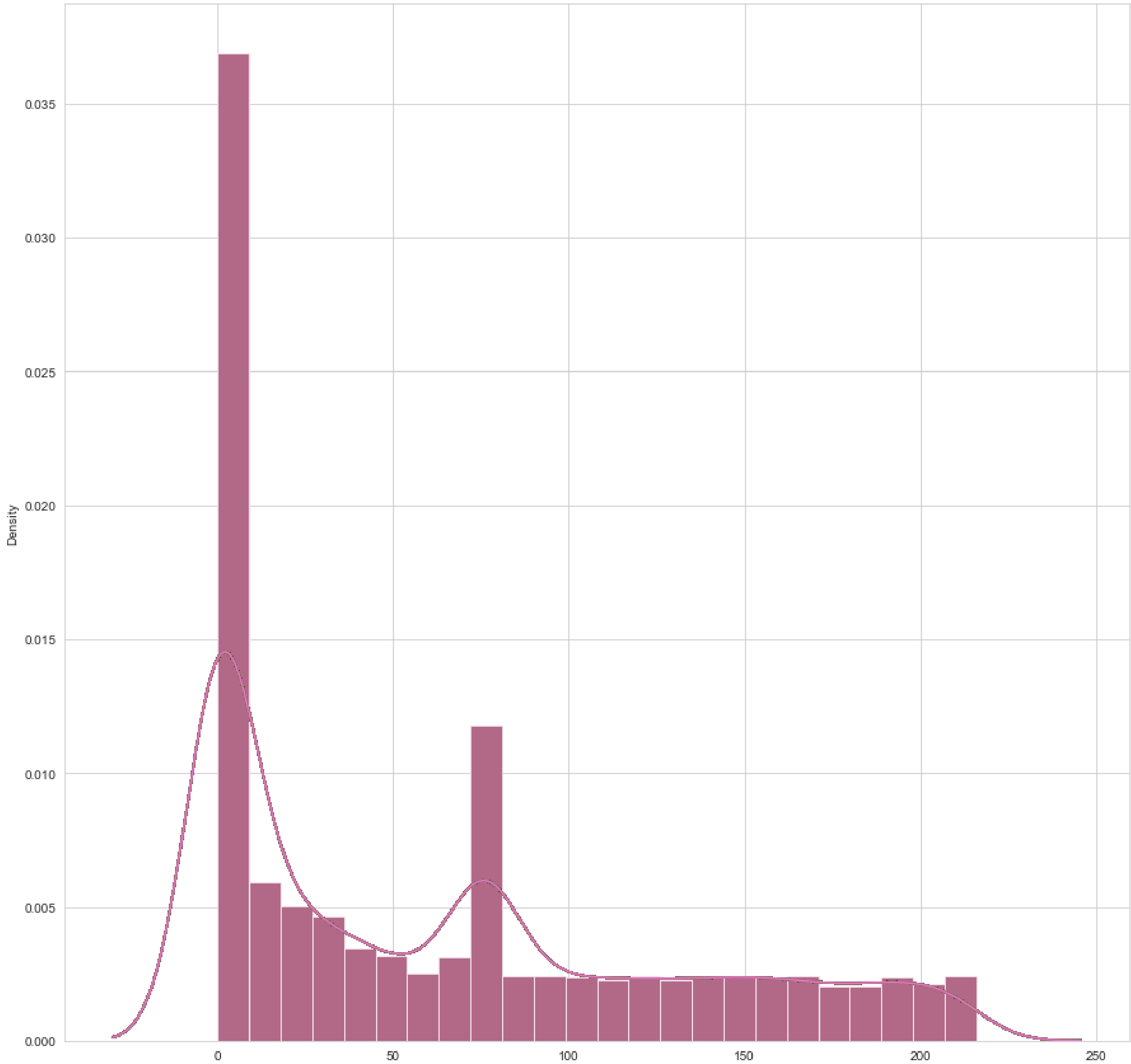
```
plt.figure(figsize=(20, 10))
sns.lineplot(x="Year", y="Value", data=df[df["Area"] == "China, mainland"])
plt.show()
```



After label encoding and outlier removal

visualization of CO2 emissions over the different countries.

```
countries = df['Area'].unique()
sns.set_style("whitegrid")
plt.figure(figsize=(15, 15))

for country in countries:
    sns.distplot(df[["Area","Value"]])
```



Part-2: EDA on Subcontinent that include Pakistan, India, and Bangladesh

> **CO2 Emissions from Subcontinent**

In this section subcontinent countries will be examined. the list of countries are as follows:

- **Bangladesh**
- **India**
- **Pakistan**

Feature Selection and Data Insights

Selecting Subcontinents countries

```
df_sub = df[df["Area"].isin(["India", "Pakistan", 'Bangladesh'])]
df_sub.head()
```

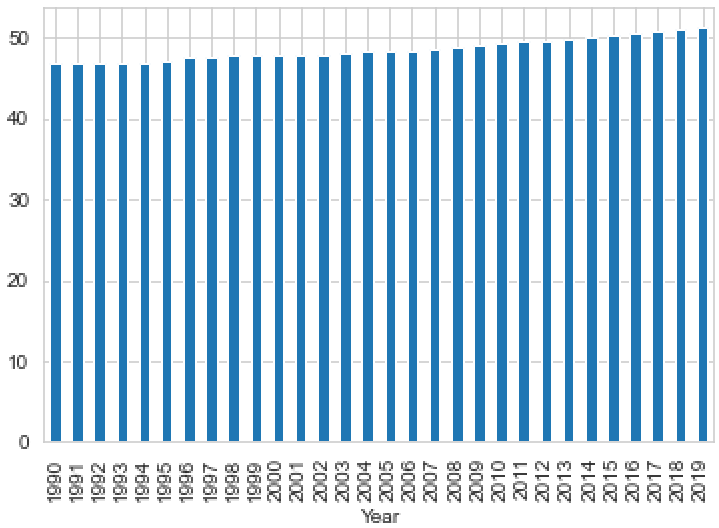
Domain Code Domain Area Code (ISO3) Area Element Code Element Item Code Item Year Code Year Unit Value Flag Flag Description 446 GW Waste Disposal BGD Bangladesh 7273 Emissions (CO2) 6990 Incineration 1990 1990 kilotonnes 46.863842 Fc Calculated data 447 GW Waste Disposal BGD Bangladesh 7273 Emissions (CO2) 6990 Incineration 1991 1991 kilotonnes 46.824124 Fc Calculated data 448 GW Waste Disposal BGD Bangladesh 7273 Emissions (CO2) 6990 Incineration 1992 1992 kilotonnes 46.870611 Fc Calculated data 449 GW Waste Disposal BGD Bangladesh 7273 Emissions (CO2) 6990 Incineration 1993 1993 kilotonnes 46.957732 Fc Calculated data 450 GW Waste Disposal BGD Bangladesh 7273 Emissions (CO2) 6990 Incineration 1994 1994 kilotonnes 46.992608 Fc Calculated data

Visualizing Subcontinents Countries Role in CO2 emissions

Study each subcontinent Country and their Comparison.

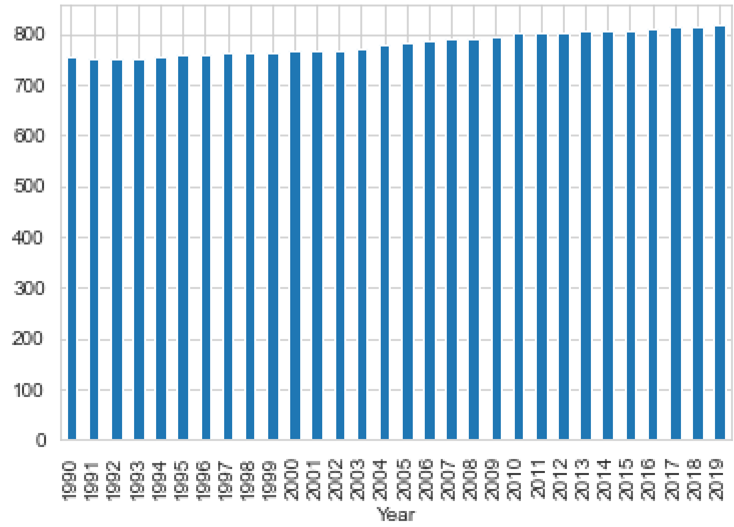
Bangladesh

```
df_sub[df_sub["Area"]=="Bangladesh"].groupby("Year")
["Value"].mean().plot(kind="bar")
```



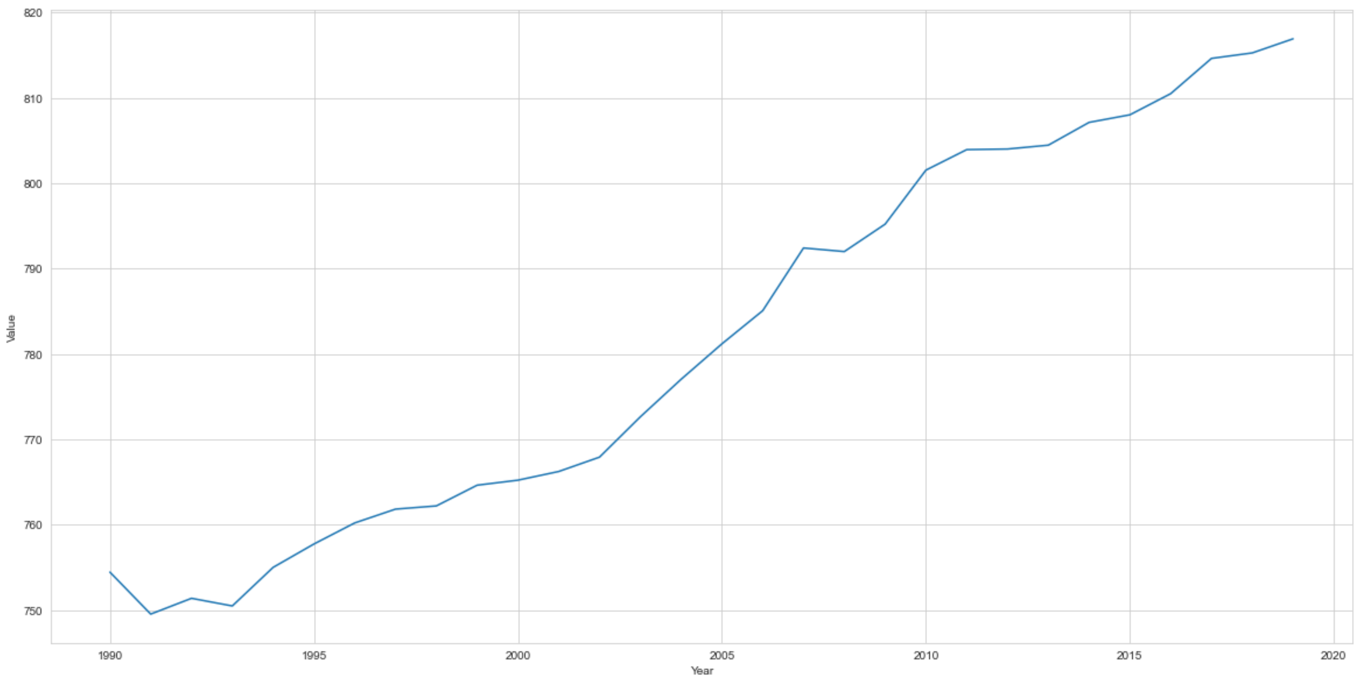
India

```
df_sub[df_sub["Area"]=="India"].groupby("Year")["Value"].mean().plot(kind="bar")
```



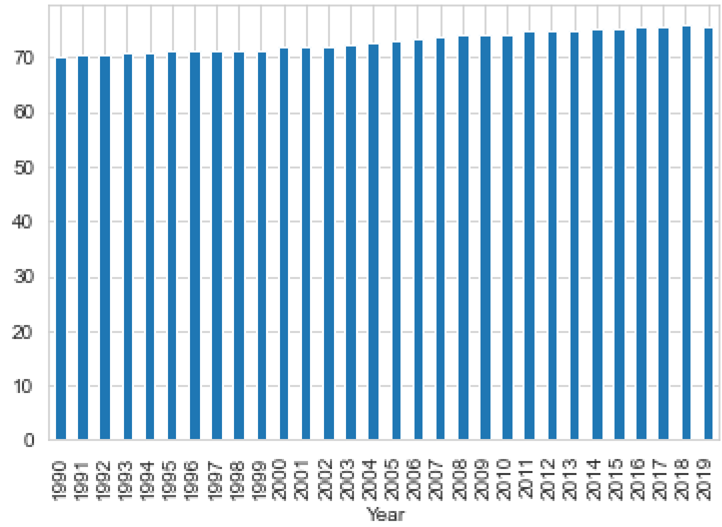
visualisation for india's energy usage increase over the years

```
plt.figure(figsize=(20, 10))
sns.lineplot(x="Year", y="Value", data=df_sub[df_sub["Area"] == "India"])
plt.show()
```



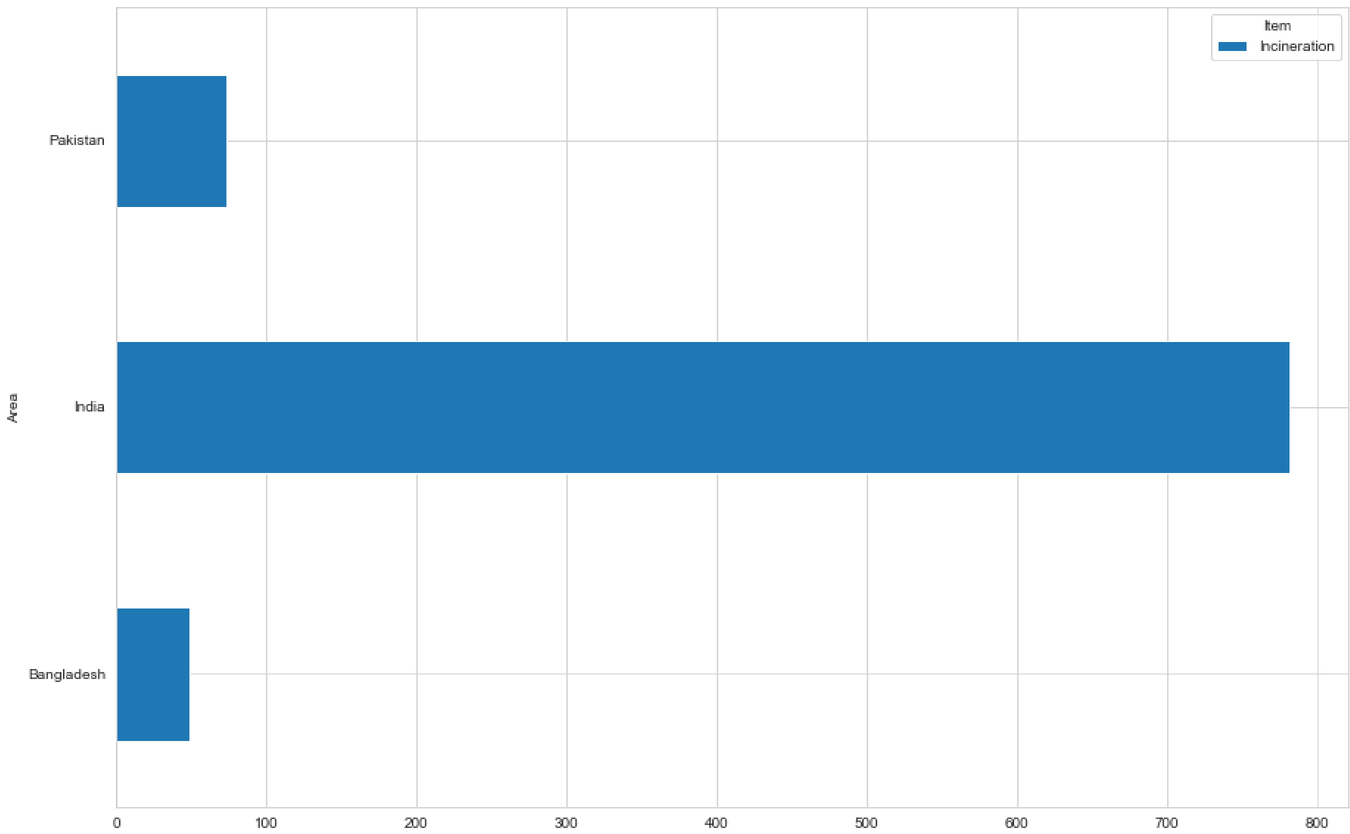
Pakistan

```
df_sub[df_sub["Area"]=="Pakistan"].groupby("Year")
["Value"].mean().plot(kind="bar")
```

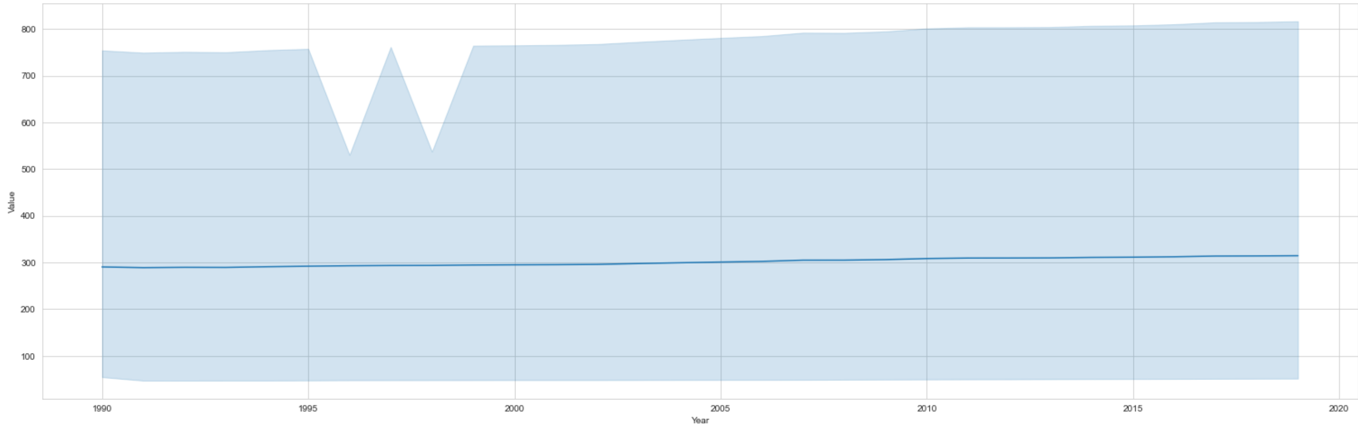


Combine

```
df_sub.groupby(['Area', 'Item'])['Value'].mean(
).unstack().plot(kind='barh', figsize=(15, 10))
```




```
plt.figure(figsize=(26, 8))
sns.lineplot(x="Year", y="Value", data=df_sub)
plt.show()
```



Conclusion

The world is releasing bulk amount of gas in atmosphere, so we need to take care of our atmospher and because it has already caused global warming as well that is current issue of the world. We have records of different courtiers and according to that, we may at least give them a warning or so to stop huge bulk of emission, do it but just some restrictions or we going to loss this world You can take recent years data and try to use different samples and different techniques. Change your perception about the comparison methodology