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```
import pandas as pd
import numpy as np
import panel as pn
pn.extension('tabulator')
import pycountry_convert as pc
import hvplot.pandas
import holoviews as hv
```

Install some libraries

pip install country_converter -upgrade

pip install dataprep

pip install pycountry-convert

```
In [224... # importing the data
    df = pd.read_csv("GCB2022v27_MtCO2_flat.csv")
    df
```

Out[224]:

:	Country	ISO 3166-1 alpha-3	Year	Total	Coal	Oil	Gas	Cement	Flaring	Other	Per Capita
0	Afghanistan	AFG	1750	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	Afghanistan	AFG	1751	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	Afghanistan	AFG	1752	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	Afghanistan	AFG	1753	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	Afghanistan	AFG	1754	0.000000	NaN	NaN	NaN	NaN	NaN	NaN	NaN
•••			•••		•••						
63099	Global	WLD	2017	36096.739276	14506.973805	12242.627935	7144.928128	1507.923185	391.992176	302.294047	4.749682
63100	Global	WLD	2018	36826.506600	14746.830688	12266.016285	7529.846784	1569.218392	412.115746	302.478706	4.792753
63101	Global	WLD	2019	37082.558969	14725.978025	12345.653374	7647.528220	1617.506786	439.253991	306.638573	4.775633
63102	Global	WLD	2020	35264.085734	14174.564010	11191.808551	7556.290283	1637.537532	407.583673	296.301685	4.497423
63103	Global	WLD	2021	37123.850352	14979.598083	11837.159116	7921.829472	1672.592372	416.525563	296.145746	4.693699

 $63104 \text{ rows} \times 11 \text{ columns}$

DATA CLEANING

In [225... df.info()

```
<class 'pandas.core.frame.DataFrame'>
          RangeIndex: 63104 entries, 0 to 63103
          Data columns (total 11 columns):
               Column
                                    Non-Null Count Dtype
                                    63104 non-null object
               Country
               ISO 3166-1 alpha-3 61472 non-null object
           2
               Year
                                    63104 non-null int64
               Total
                                     62904 non-null float64
               Coal
                                    21744 non-null float64
           5
               Oil
                                    21717 non-null float64
           6
               Gas
                                    21618 non-null float64
                                    20814 non-null float64
               Cement
           8
               Flaring
                                    21550 non-null float64
                                    1620 non-null float64
               Other
           10 Per Capita
                                    18974 non-null float64
          dtypes: float64(8), int64(1), object(2)
          memory usage: 5.3+ MB
In [226... df.describe()
                                                                 Oil
                                                                                                                 Other
                                                                                                                          Per Capita
Out[226]:
                         Year
                                      Total
                                                   Coal
                                                                             Gas
                                                                                       Cement
                                                                                                    Flaring
           count 63104.000000 62904.000000 21744.000000
                                                        21717.000000 21618.000000 20814.000000 21550.000000 1620.000000 18974.000000
                  1885.500000
                                  55.224788
                                              73.968916
                                                                                      4.330443
                                                                                                   1.712695
                                                                                                              10.951389
                                                                                                                           4.413363
           mean
                                                           55.760624
                                                                        23.504285
                     78.519728
                                 824.845435
                                             598.986992
                                                          519.034563
                                                                       247.674772
                                                                                     50.305770
                                                                                                  16.727067
                                                                                                             39.034073
                                                                                                                           17.432815
                   1750.000000
                                  0.000000
                                               0.000000
                                                            0.000000
                                                                         0.000000
                                                                                      0.000000
                                                                                                   0.000000
                                                                                                              0.000000
                                                                                                                           0.000000
             min
                   1817.750000
                                  0.000000
                                               0.000000
                                                            0.091600
                                                                         0.000000
                                                                                      0.000000
                                                                                                   0.000000
                                                                                                              0.520885
                                                                                                                           0.197866
            25%
                  1885.500000
                                  0.000000
                                                0.271852
                                                            1.044240
                                                                         0.000000
                                                                                      0.022756
                                                                                                   0.000000
                                                                                                               1.255329
            50%
                                                                                                                           1.303949
                  1953.250000
                                  0.549342
                                                6.736411
                                                                                      0.568502
                                                                                                   0.000000
                                                                                                               4.385471
            75%
                                                            8.339752
                                                                         0.581628
                                                                                                                           5.077994
                  2021.000000 37123.850352 15051.512770 12345.653374
                                                                      7921.829472
                                                                                   1672.592372
                                                                                                 439.253991
                                                                                                            306.638573
                                                                                                                         834.192642
In [227... # Checks total duplicate rows
          duplicate = df.duplicated(keep=False).sum()
          duplicate
Out[227]: 0
In [228...
          ## check how many columns contains null values
          df.isnull().sum().sort_values()
           Country
Out[228]:
           Year
                                      0
                                    200
           Total
           ISO 3166-1 alpha-3
                                   1632
           Coal
                                  41360
           Oil
                                  41387
           Gas
                                  41486
                                  41554
           Flaring
           Cement
                                  42290
           Per Capita
                                  44130
                                  61484
           Other
           dtype: int64
```

df.fillna(0, inplace = True)

Asumming that if a country does not have a

In [229...

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```
In []: # some countries places in the dataset are not countires, so i dropped them.
    indexAge = df[ (df['Country'] == "St. Kitts-Nevis-Anguilla")].index
    df.drop(indexAge, inplace=True)
    df.head(15)

In []: df["Country"].unique()

In [371... df.to_csv('file1.csv')

In [387... df.rename(columns={"Total": "Total_CO2"}, inplace=True)

In [366... # Make DataFrame Pipeline Interactive
    idf = df.interactive()
```

map each country to its continent

```
In [247... # see the pycountry_ onverter documentation
          def convert (row):
              # convert country name to country code
              cn_code = pc.country_name_to_country_alpha2(row.Country, cn_name_format= "default")
              # convert country code to continent code
             conti_code = pc.country_alpha2_to_continent_code(cn_code)
             return conti code
In [275... # crete a new column with continent code
          df["continent"] = df.apply(convert, axis = 1)
In [276... df["continent"].unique()
          array(['AS', 'EU', 'AF', 'NA', 'SA', 'OC'], dtype=object)
Out[276]:
In [277... # map continent code to continent name
          conti_name = {"AS": "Asia",
                       "SA": "South America",
                       "EU": "Europe",
                       "AF": "Africa",
                       "NA": "North America",
                       "OC": "Oceania"}
          df["continent"] = df["continent"].map(conti_name)
```

CO2 emission over time by continent

```
button_type='success'
          yaxis_Total_CO2
Out[420]:
                                                 Total_CO2
 In [ ]: co2_pipeline = (
              idf[
                  (idf.Year <= year slider)</pre>
              .groupby(['continent', 'Year'])["Total_CO2"].mean()
              .to frame()
              .reset_index()
              .sort_values(by='Year')
              .reset_index(drop=True)
          co2 pipeline
In [421... # plot grapgh using the c02 pipeline
          co2_plot = co2_pipeline.hvplot(x = 'Year', by='continent', y=yaxis_Total_CO2,line_width=2, title="CO2 emission by continent")
          co2_plot
```



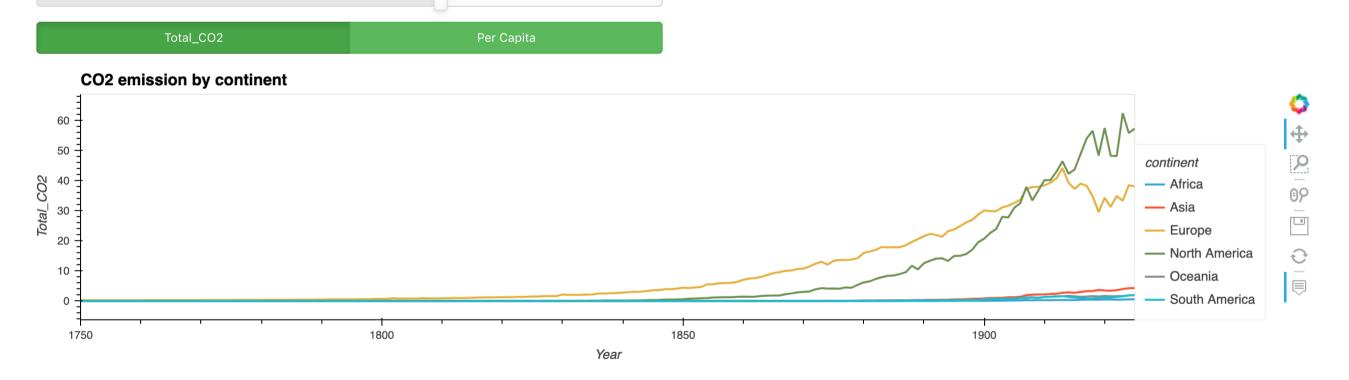


Table - CO2 emission over time by continent

```
In [392... co2_table = co2_pipeline.pipe(pn.widgets.Tabulator, pagination='remote', page_size = 9, sizing_mode='stretch_width') co2_table
```

Out [392]: Year slider: **1990**

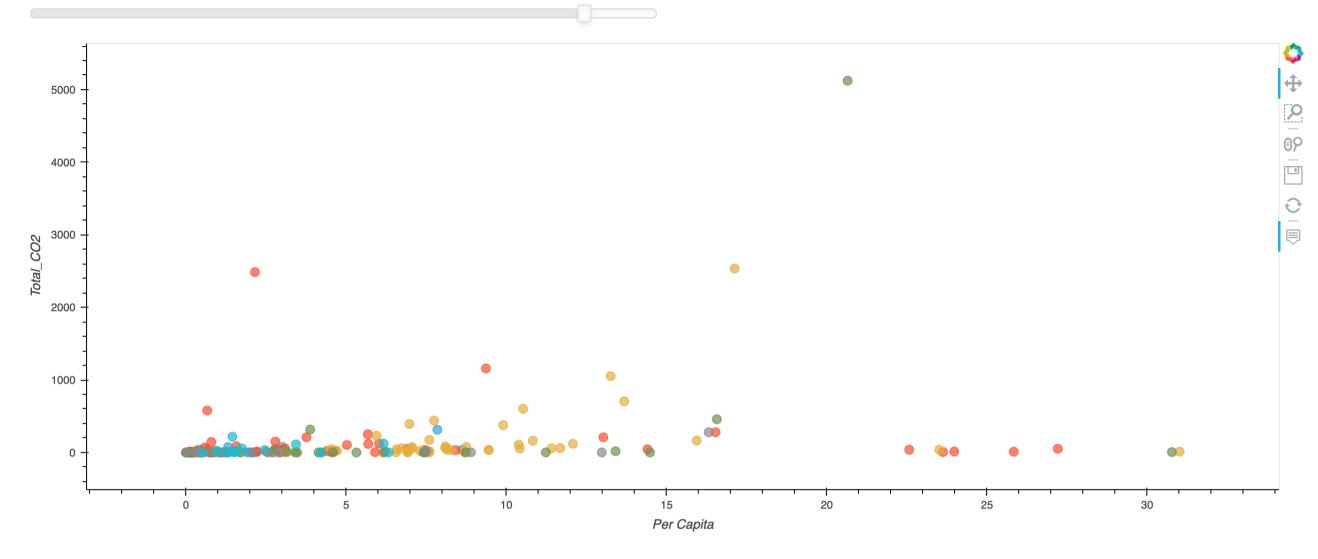
index 🔺	continent _	Year 🔺	Total_CO2 _
0	Africa	1,750	0.0
1	Oceania	1,750	0.0
2	North America	1,750	0.0
3	Europe	1,750	0.233763
4	Asia	1,750	0.0
5	South America	1,750	0.0
6	North America	1,751	0.0
7	South America	1,751	0.0
8	Europe	1,751	0.233763

CO2 vs GDP scatterplot

```
In [ ]: co2_vs_per_capita_scatterplot_pipeline = (
             idf[
                  (idf.Year == year_slider)
              .groupby(['continent', 'Year', 'Per Capita'])['Total_CO2'].mean()
              .to_frame()
              .reset index()
              .sort_values(by='Year')
              .reset index(drop=True)
         co2_vs_per_capita_scatterplot_pipeline
In [424... co2_vs_per_capita_scatterplot = co2_vs_gdp_scatterplot_pipeline.hvplot(x='Per Capita',
                                                                          y='Total_CO2',
                                                                          by='continent',
                                                                          size=80, kind="scatter",
                                                                          alpha=0.7,
                                                                          legend=False,
                                                                          height=500,
                                                                          width=500)
         co2_vs_per_capita_scatterplot
```

First Prev 1 2 3 4 5 Next Last

Out [424]: Year slider: 1990



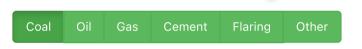
Bar chart with CO2 sources by continent

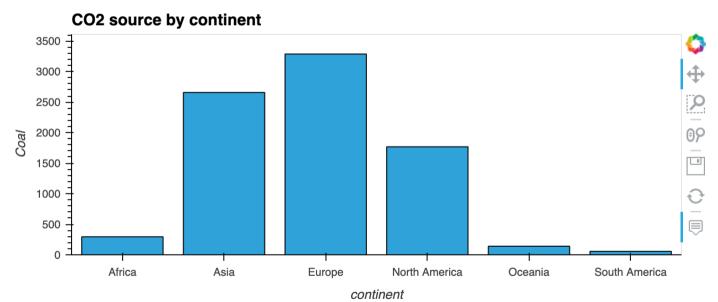
Out [394]: Year slider: 1990



	Year	continent	Coal
0	1990	Africa	295.753071
1	1990	Asia	3252.448897
2	1990	Europe	2980.499273
3	1990	North America	1930.964950
4	1990	Oceania	147.035089
5	1990	South America	66.518716

Out [342]: Year slider: **1985**





Creating Dashboard