Tutorials

Handle, Describe, and Plot the EM-DAT Data

- 1: Python Tutorial 1: Basic Operations and Plotting
- 2: Python Tutorial 2: Making Maps

1 - Python Tutorial 1: Basic Operations and Plotting

This tutorial shows basic examples on how to load, handle, and plot the EM-DAT data using the `pandas` Python data analysis package and the `matplotlib` charting library.

Note: The Jupyter Notebook version of this tutorial is available on the EM-DAT Python Tutorials GitHub Repository.

Import Modules

Let us import the necessary modules and print their versions. For this tutorial, we used `pandas` v.2.1.1 and `matplotlib` v.3.8.3. If your package versions are different, you may have to adapt this tutorial by checking the corresponding package documentation.

```python
import pandas as pd #data analysis package
import matplotlib as mpl
import matplotlib.pyplot as plt #plotting library
for i in [pd, mpl]:
    print(i.__name__, i.__version__)
```

```
pandas 2.1.1
matplotlib 3.8.3
```

Load EM-DAT

To load EM-DAT:

- Download the EM-DAT data at https://public.emdat.be/ (registration is required, see the EM-DAT Documentation page on Data Accessibility);
- Use the pd.read_excel method to load and parse the data into a `pd.DataFrame` object;
- Check if the data has been successfully parsed with the `pd.DataFrame.info` method.

Notes:

1. You may need to install the `openpyxl` package or another engine to make it possible to read the data.
2. Another option is to export the `.xlsx` file into a `.csv`, and use the `pd.read_csv` method;
3. If not in the same folder as the Python code, replace the filename with the relative path or the full path, e.g., `E:/MyDATa/public_emdat_2024-01-08.xlsx`

```
#!pip install openpyxl
df = pd.read_excel('public_emdat_2024-01-08.xlsx') # <-- modify fil
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15560 entries, 0 to 15559
Data columns (total 46 columns):
 #   Column                                    Non-Null Count  Dty
---  ------                                    --------------  ---
 0   DisNo.                                    15560 non-null  obj
 1   Historic                                  15560 non-null  obj
 2   Classification Key                        15560 non-null  obj
 3   Disaster Group                            15560 non-null  obj
 4   Disaster Subgroup                         15560 non-null  obj
 5   Disaster Type                             15560 non-null  obj
 6   Disaster Subtype                          15560 non-null  obj
 7   External IDs                              2371 non-null   obj
 8   Event Name                                4904 non-null   obj
 9   ISO                                       15560 non-null  obj
 10  Country                                   15560 non-null  obj
 11  Subregion                                 15560 non-null  obj
 12  Region                                    15560 non-null  obj
 13  Location                                  14932 non-null  obj
 14  Origin                                    3864 non-null   obj
 15  Associated Types                          3192 non-null   obj
 16  OFDA Response                             15560 non-null  obj
 17  Appeal                                    15560 non-null  obj
 18  Declaration                               15560 non-null  obj
 19  AID Contribution ('000 US$)               490 non-null    flo
 20  Magnitude                                 3356 non-null   flo
 21  Magnitude Scale                           9723 non-null   obj
 22  Latitude                                  1809 non-null   flo
 23  Longitude                                 1809 non-null   flo
 24  River Basin                               1197 non-null   obj
 25  Start Year                                15560 non-null  int
 26  Start Month                               15491 non-null  flo
 27  Start Day                                 14068 non-null  flo
 28  End Year                                  15560 non-null  int
 29  End Month                                 15401 non-null  flo
```

```
 30   End Day                                          14132 non-null  flo
 31   Total Deaths                                     12485 non-null  flo
 32   No. Injured                                      5694 non-null   flo
 33   No. Affected                                     7046 non-null   flo
 34   No. Homeless                                     1312 non-null   flo
 35   Total Affected                                   11508 non-null  flo
 36   Reconstruction Costs ('000 US$)                  33 non-null     flo
 37   Reconstruction Costs, Adjusted ('000 US$)        29 non-null     flo
 38   Insured Damage ('000 US$)                        691 non-null    flo
 39   Insured Damage, Adjusted ('000 US$)              683 non-null    flo
 40   Total Damage ('000 US$)                          3070 non-null   flo
 41   Total Damage, Adjusted ('000 US$)                3020 non-null   flo
 42   CPI                                              15056 non-null  flo
 43   Admin Units                                      8336 non-null   obj
 44   Entry Date                                       15560 non-null  obj
 45   Last Update                                      15560 non-null  obj
dtypes: float64(20), int64(2), object(24)
memory usage: 5.5+ MB
```

Example 1: Japan Earthquake Data

Filtering

Let us focus on the EM-DAT earthquakes in Japan from the years 2000 to 2003 and create a suitable filter utilizing the EM-DAT columns `Disaster Type`, `ISO` and `Start Year`.

For simplicity, let's retain only the columns `Start Year`, `Magnitude`, and `Total Deaths` and display the first five entries using the `pd.DataFrame.head` method.

Note: For further details about the columns, we refer to the EM-DAT Documentation page EM-DAT Public Table.

```
eq_jpn = df[
    (df['Disaster Type'] == 'Earthquake') &
    (df['ISO'] == 'JPN') &
```

```
    (df['Start Year'] < 2024)
][['Start Year', 'Magnitude', 'Total Deaths', 'Total Affected']]
eq_jpn.head(5)
```

	Start Year	Magnitude	Total Deaths	Total Affected
392	2000	6.1	1.0	100.0
610	2000	6.7	NaN	7132.0
1013	2001	6.8	2.0	11261.0
2791	2003	7.0	NaN	2303.0
2884	2003	5.5	NaN	18191.0

Grouping

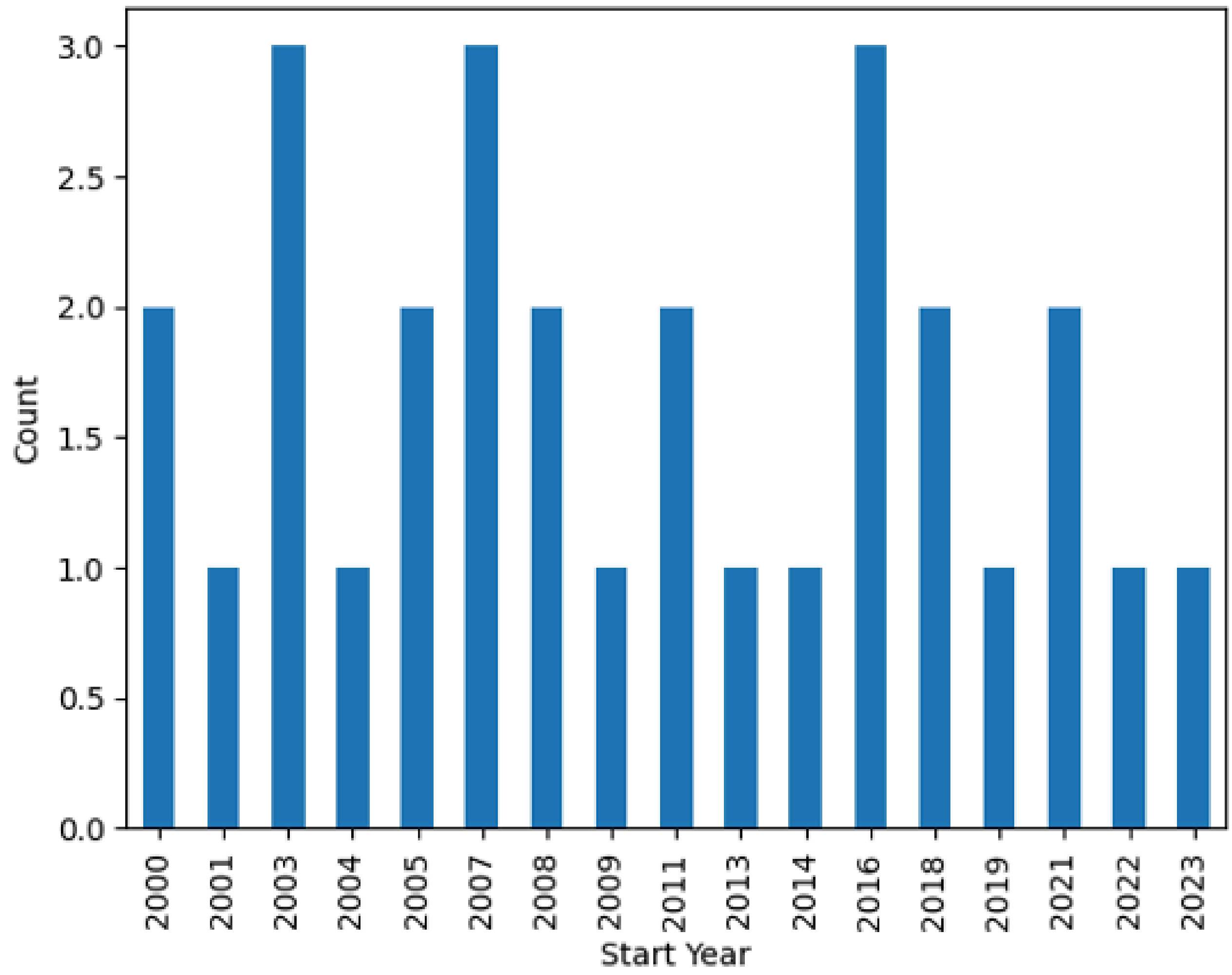
Let us group the data to calculate the number of earthquake events by year and plot the results.

- Use the `groupby` method to group based on one or more columns in a DataFrame, e.g., `Start Year`;
- Use the `size` method as an aggregation method (or `count`).
- Plot the results using the `pd.DataFrame.plot` method.

Note: The `count` method provides the total number of non-missing values, while `size` gives the total number of elements (including missing values). Since the field `Start Year` is always defined, both methods should return the same results.

```
eq_jpn.groupby(['Start Year']).size().plot(kind='bar', ylabel='Coun
```

```
<Axes: xlabel='Start Year', ylabel='Count'>
```



Output plot

Customize Chart

The `pandas` library relies on the `matplotlib` package to draw charts. To have more flexibility on the rendered chart, let us create the figure using the imported `plt` submodule.

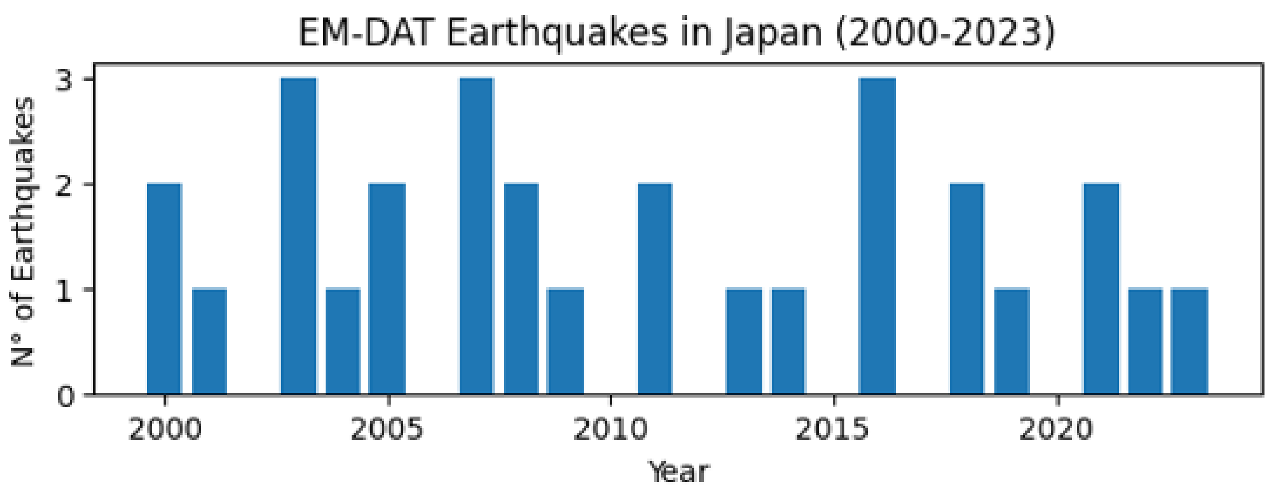
```
# Group earthquake data by 'Start Year' and count occurrences
eq_cnt = eq_jpn.groupby(['Start Year']).size()

# Initialize plot with specified figure size
fig, ax = plt.subplots(figsize=(7, 2))

# Plot number of earthquakes per year
ax.bar(eq_cnt.index, eq_cnt)
```

```
# Set axis labels and title
ax.set_xlabel('Year')
ax.set_ylabel('N° of Earthquakes')
ax.set_yticks([0, 1, 2, 3])  # Define y-axis tick marks
ax.set_title('EM-DAT Earthquakes in Japan (2000-2023)')
```

```
Text(0.5, 1.0, 'EM-DAT Earthquake in Japan (2000-2023)')
```



Output plot

Example 2: Comparing Regions

Let us compare earthquake death toll by continents. As before, we filter the original dataframe `df` according to our specific needs, including the `Region` column.

```
eq_all = df[
    (df['Disaster Type'] == 'Earthquake') &
    (df['Start Year'] < 2024)
][['Start Year', 'Magnitude', 'Region', 'Total Deaths', 'Total Affe
eq_all.head(5)
```

	Start Year	Magnitude	Region	Total Deaths	Total Affected
23	2000	4.3	Asia	NaN	1000.0
33	2000	5.9	Asia	7.0	1855007.0
36	2000	4.9	Asia	1.0	10302.0
41	2000	5.1	Asia	NaN	62030.0
50	2000	5.3	Asia	1.0	2015.0

In this case,

- Use the `groupby` method to group based on the `Region` column;
- Use the `sum` method for the `Total Deaths` field as aggregation method;
- Plot the results easilly using the `pd.DataFrame.plot` method.

```
eq_sum = eq_all.groupby(['Region'])['Total Deaths'].sum()
eq_sum
```

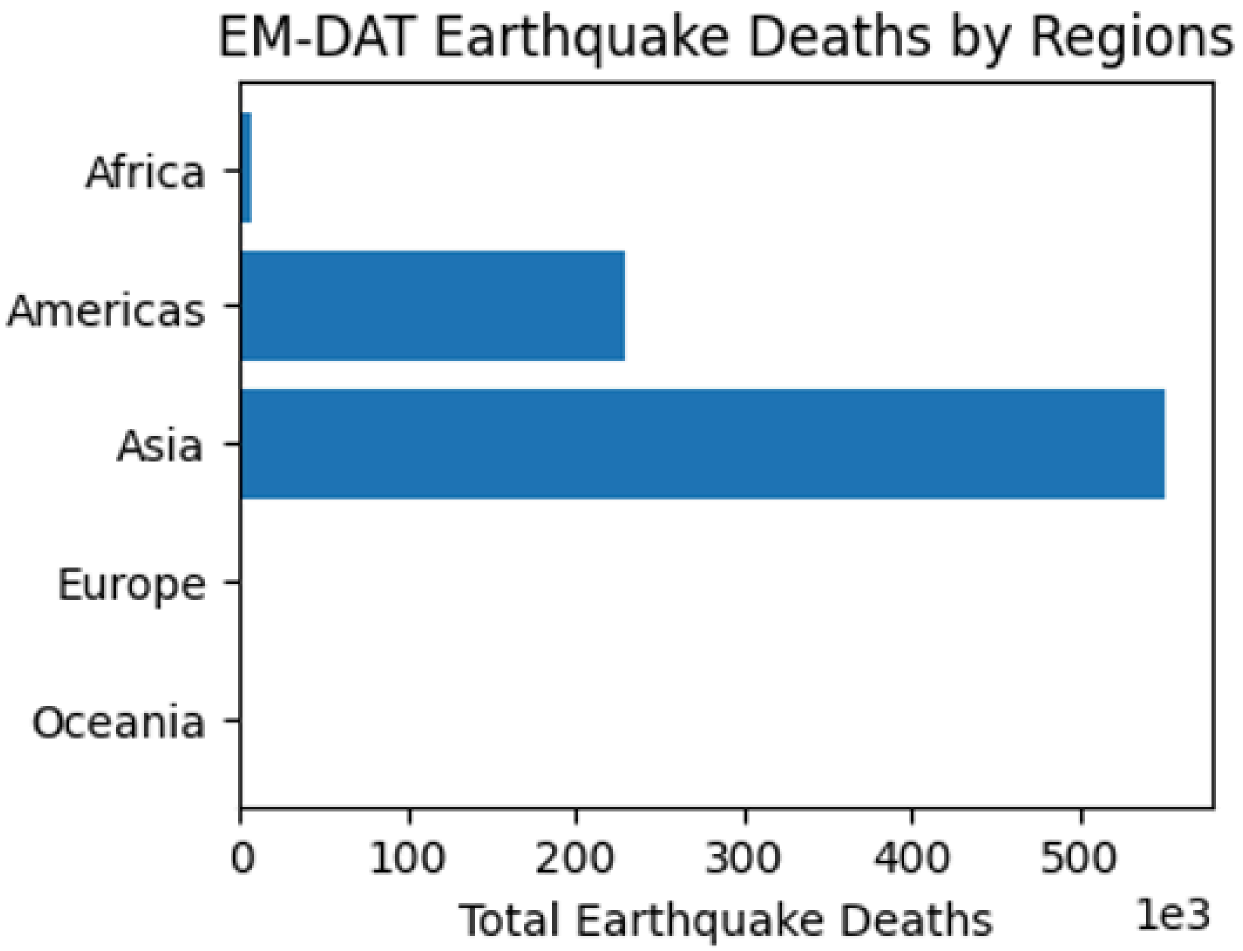
```
Region
Africa        5863.0
Americas    229069.0
Asia        548766.0
Europe         783.0
Oceania        641.0
Name: Total Deaths, dtype: float64
```

Finally, let us make an horizontal bar chart of it using `matplotlib` . In particular,

- use the `ax.ticklabel_format` method to set the x axis label as scientific (in thousands of deaths);
- use the `ax.invert_yaxis` to display the regions in alphabetical order from top to bottom.

```
fig, ax = plt.subplots(figsize=(4,3))
ax.barh(eq_sum.index, eq_sum)
ax.set_xlabel('Total Earthquake Deaths')
ax.ticklabel_format(style='sci',scilimits=(3,3),axis='x')
ax.invert_yaxis()
ax.set_title('EM-DAT Earthquake Deaths by Regions')
```

```
Text(0.5, 1.0, 'EM-DAT Earthquake Deaths by Regions')
```



Output plot

Example 3: Multiple Grouping

At last, let us report the earthquake time series by continents. To avoid the creation of a `['Region', 'Start Year']` multiindex for future processing, we set the argument `as_index` to `False`. As such, `Region` and `Start Year` remain columns.

```
eq_reg_ts = eq_all.groupby(
    ['Region', 'Start Year'], as_index=False
)['Total Deaths'].sum()
eq_reg_ts
```

	Region	Start Year	Total Deaths
0	Africa	2000	1.0
1	Africa	2001	0.0
2	Africa	2002	47.0
3	Africa	2003	2275.0
4	Africa	2004	943.0
...	...	...	...
92	Oceania	2016	2.0
93	Oceania	2018	181.0
94	Oceania	2019	0.0
95	Oceania	2022	7.0
96	Oceania	2023	8.0

97 rows × 3 columns

Next, we apply the `pivot` method to restructure the table in a way it could be plot easilly.

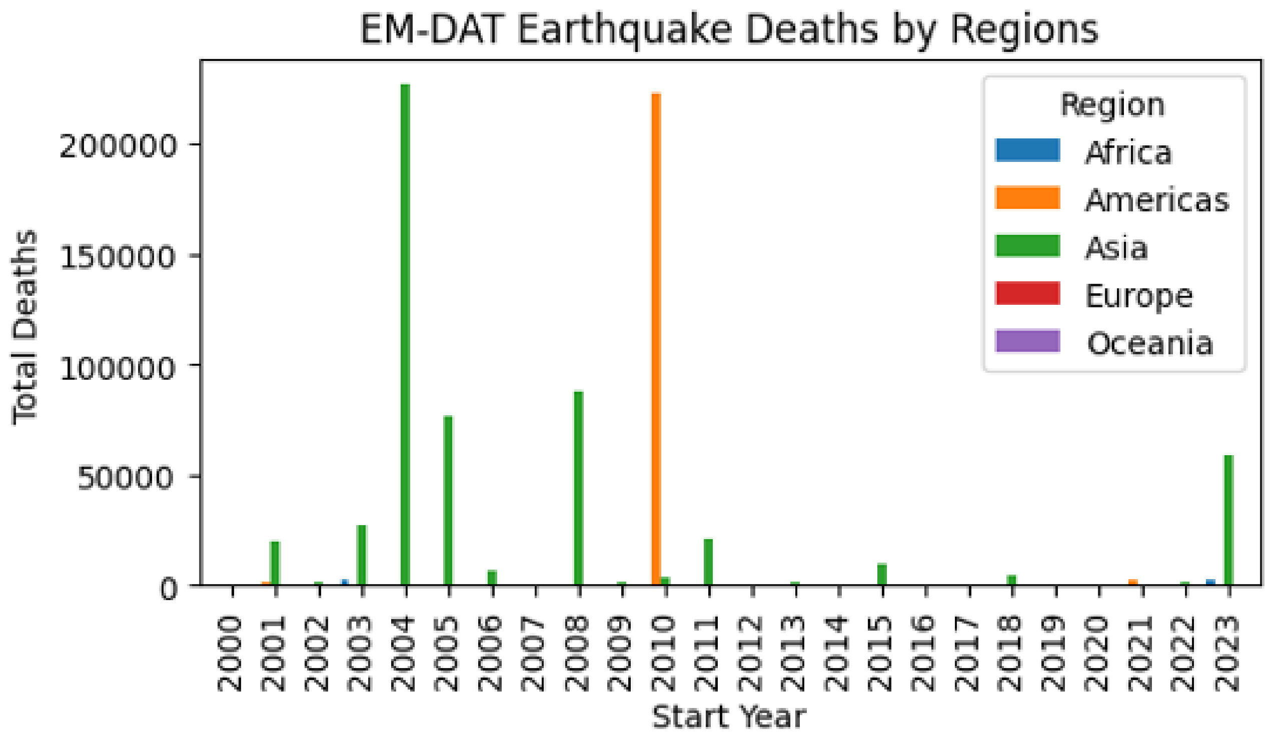
```
eq_pivot_ts = eq_reg_ts.pivot(
    index='Start Year', columns='Region', values='Total Deaths'
```

```
)
eq_pivot_ts.head()
```

Region	Africa	Americas	Asia	Europe	Oceania
Start Year					
2000	1.0	9.0	205.0	0.0	2.0
2001	0.0	1317.0	20031.0	0.0	0.0
2002	47.0	0.0	1554.0	33.0	5.0
2003	2275.0	38.0	27301.0	3.0	NaN
2004	943.0	10.0	226336.0	1.0	NaN

```
ax = eq_pivot_ts.plot(kind='bar', width=1, figsize=(6,3))
ax.set_ylabel('Total Deaths')
ax.set_title('EM-DAT Earthquake Deaths by Regions')
```

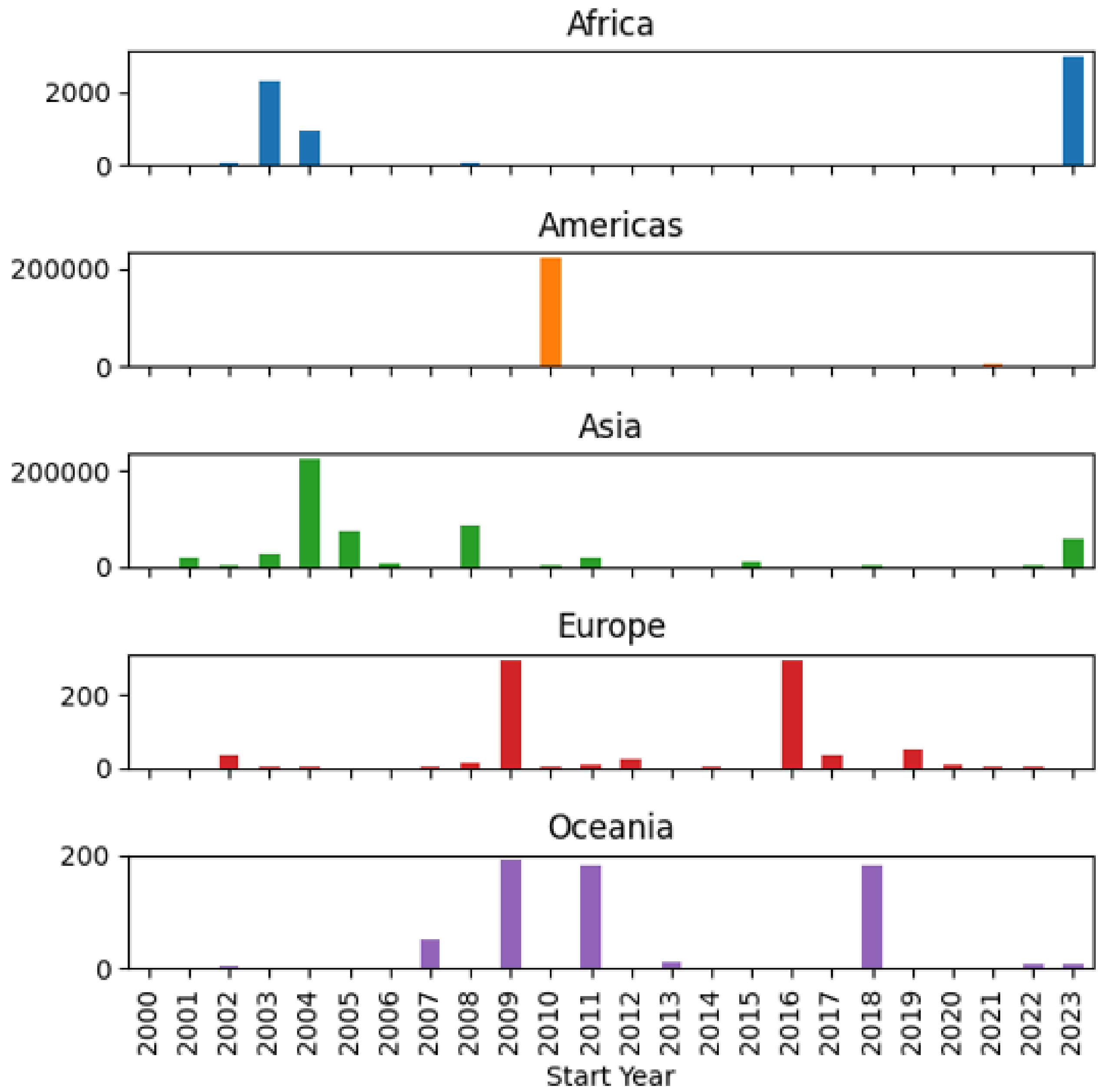
```
Text(0.5, 1.0, 'EM-DAT Earthquake Deaths by Regions')
```



Output plot

In order to be able to visualize the data in more details, let us make a subplot instead by setting the `subplot` argument to `True` within the `plot` method.

```
ax = eq_pivot_ts.plot(kind='bar', subplots=True, legend=False, figs
plt.tight_layout() # <-- adjust plot layout
```



Output plot

We have just covered the most common manipulations applied to a `pandas` `DataFrame` containing the EM-DAT data. To delve further into your analyses, we encourage you to continue your learning of pandas and matplotlib with the many resources available online, starting with the official documentation.

If you are interested in learning the basics of making maps based on EM-DAT data, you can also follow the second EM-DAT Python Tutorial.

2 - Python Tutorial 2: Making Maps

If you have followed the first EM-DAT Python Tutorial 1 or are already familiar with `pandas` and `matplotlib`, this second tutorial will show you basic examples on how to make maps with the EM-DAT data using the `geopandas` Python package.

Note: The Jupyter Notebook version of this tutorial is available on the EM-DAT Python Tutorials GitHub Repository.

Import Modules

Let us import the necessary modules and print their versions. For this tutorial, we used `pandas` v.2.1.1, `geopandas` v.0.14.3, and `matplotlib` v.3.8.3. If your package versions are different, you may have to adapt this tutorial by checking the corresponding package documentation.

```python
import pandas as pd #data analysis package
import geopandas as gpd
import matplotlib as mpl
import matplotlib.pyplot as plt #plotting library
for i in [pd, gpd, mpl]:
    print(i.__name__, i.__version__)
```

```
pandas 2.2.1
geopandas 0.14.3
matplotlib 3.8.3
```

Creating a World Map

To create a world map, we need the EM-DAT data and a shapefile containing the country geometries.

EM-DAT: We download and load the EM-DAT data using `pandas`.

Country Shapefile: We download a country shapefile from Natural Earth Data. For a world map, we download the low resolution 1:110m Adimin 0 - Countries (last accessed: March 10, 2024) and unzip it.

Load and Filter EM-DAT

Let us load EM-DAT and filter it to make a global map of Earthquake disasters between 2000 and 2023. We calculate the number of unique identifiers (`DisNo.`) per country (`ISO`) We refer to the standard `ISO` column instead of the `Country` column of the EM-DAT Public Table to be able to make a join with the country shapefile.

```
df = pd.read_excel('public_emdat_2024-01-08.xlsx')
earthquake_counts = df[
    (df['Disaster Type'] == 'Earthquake') &
    (df['Start Year'] < 2024)
].groupby('ISO')["DisNo."].count().reset_index(name='EarthquakeCoun
earthquake_counts
```

	ISO	EarthquakeCount
0	AFG	21
1	ALB	4
2	ARG	2
3	ASM	1
4	AZE	3
...	...	...
86	USA	10
87	UZB	1

	ISO	EarthquakeCount
88	VUT	2
89	WSM	1
90	ZAF	2

91 rows × 2 columns

Load the Country Shapefile

We use the `gpd.read_file` method to load the country shapefile and parse it into a geodataframe. A geodataframe is similar to a `pandas` dataframe, extept that has a geometry column.

We provide the `filename` argument, which is either a file name if located in the same directory than the running script, or a relative or absolute path, if not. In our case the shapefile with the `.shp` extension is located in the `ne_110m_admin_0_countries` folder.

Since the geodataframe contains 169 columns, we only keep the two column that we are interrested in, i.e., `ISO_A3` and `geometry`.

```
gdf = gpd.read_file ('ne_110m_admin_0_countries/ne_110m_admin_0_cou
gdf = gdf[['ISO_A3', 'geometry']]
gdf
```

```
Cannot find header.dxf (GDAL_DATA is not defined)
```

	ISO_A3	geometry
0	FJI	MULTIPOLYGON (((180.00000 -16.06713, 180.00000...
1	TZA	POLYGON ((33.90371 -0.95000, 34.07262 -1.05982...

	ISO_A3	geometry
2	ESH	POLYGON ((-8.66559 27.65643, -8.66512 27.58948...
3	CAN	MULTIPOLYGON (((-122.84000 49.00000, -122.9742...
4	USA	MULTIPOLYGON (((-122.84000 49.00000, -120.0000...
...	...	...
172	SRB	POLYGON ((18.82982 45.90887, 18.82984 45.90888...
173	MNE	POLYGON ((20.07070 42.58863, 19.80161 42.50009...
174	-99	POLYGON ((20.59025 41.85541, 20.52295 42.21787...
175	TTO	POLYGON ((-61.68000 10.76000, -61.10500 10.890...
176	SSD	POLYGON ((30.83385 3.50917, 29.95350 4.17370, ...

177 rows × 2 columns

Important Notice: Above, some geometries do not have a ISO code, such as the one at row 174. Below, you will see that some ISO in EM-DAT are not matched with a geometries. Beyond this basic tutorial, we advice to carefully evaluate these correspondance and non-correspondance between ISO codes and to read the EM-DAT Documentation about ISO codes.

Join the Two Datasets

Let us merge the two dataset with an outer join, using the `merge` method. We prefer an `outer` join to keep the geometries of countries for which EM-DAT has no records.

```
earthquake_counts_with_geom = gdf.merge(
    earthquake_counts, left_on='ISO_A3', right_on='ISO', how='outer
earthquake_counts_with_geom
```

	ISO_A3	geometry	ISO	EarthquakeCount
0	-99	MULTIPOLYGON (((15.14282 79.67431, 15.52255 80...	NaN	NaN
1	-99	MULTIPOLYGON (((-51.65780 4.15623, -52.24934 3...	NaN	NaN
2	-99	POLYGON ((32.73178 35.14003, 32.80247 35.14550...	NaN	NaN
3	-99	POLYGON ((48.94820 11.41062, 48.94820 11.41062...	NaN	NaN
4	-99	POLYGON ((20.59025 41.85541, 20.52295 42.21787...	NaN	NaN
...	...	...	...	...
185	NaN	None	WSM	1.0
186	YEM	POLYGON ((52.00001 19.00000, 52.78218 17.34974...	NaN	NaN
187	ZAF	POLYGON ((16.34498 -28.57671, 16.82402 -28.082...	ZAF	2.0
188	ZMB	POLYGON ((30.74001 -8.34001, 31.15775 -8.59458...	NaN	NaN
189	ZWE	POLYGON ((31.19141 -22.25151, 30.65987 -22.151...	NaN	NaN

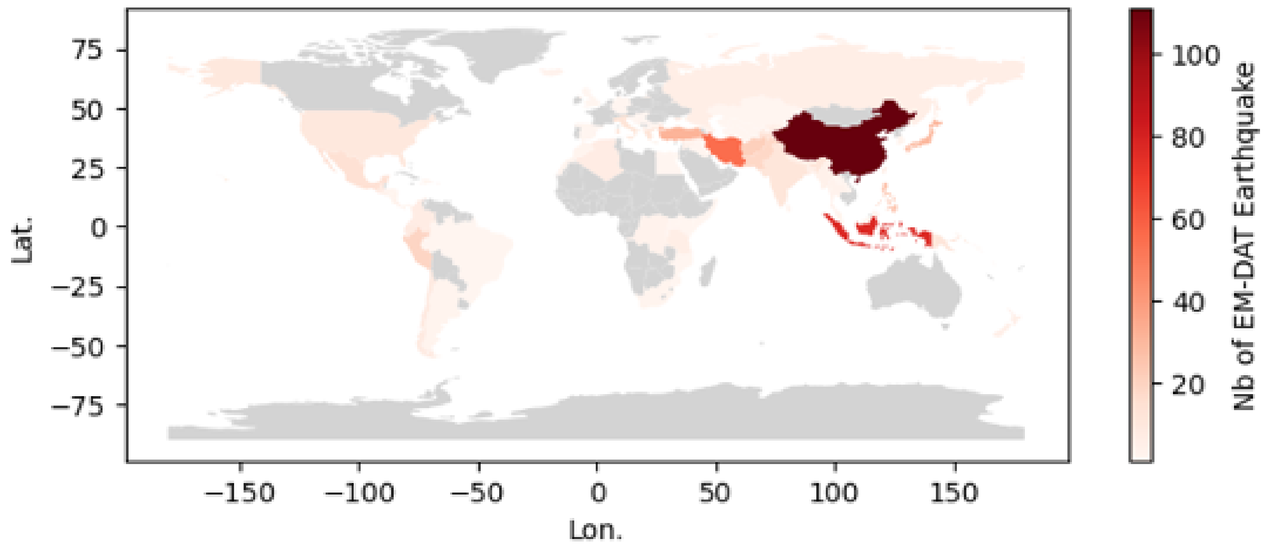
190 rows × 4 columns

Make the Map

To make the map, we use the `geopandas` built-in API, through the `plot` method built on the top of `matplotlib` . Below, we show an hybrid plotting approach and first create an empty figure `fig` and `ax` object with matplotlib before passing the `ax` object as an argument within the `plot` method. This approach gives more control to users familiar with `matplotlib` to further customize the chart.

```
fig, ax = plt.subplots(figsize=(8,3))
earthquake_counts_with_geom.plot(
    column='EarthquakeCount',
    ax=ax,
    cmap='Reds',
```

```
        vmin=1,
        legend=True,
        legend_kwds={"label": "Nb of EM-DAT Earthquake"},
        missing_kwds= dict(color = "lightgrey",)
)
_ = ax.set_xlabel('Lon.')
_ = ax.set_ylabel('Lat.')
```



Output plot

Creating a Map at Admin Level 1

We can create a more detailed map using the `Admin Units` column in the EM-DAT Public Table. This column contains the identifiers of administrative units of level 1or 2 as defined by the Global Administrative Unit Layer (GAUL) for country impacted by non-biological natural hazards.

Similarly to the country map, we need to download a file containing GAUL geometries. The file corresponds to the last version of GAUL published in 2015. In this tutorial, we will focus on Japanese earthquake occurrence in EM-DAT.

Note: the file size is above 1.3Go and requires a performant computer to process in Python. Using a Geographical Information Software (GIS) for the preprocessing is another option.

Load the Admin Units Geopackage

The file is a geopackage `.gpkg` that contains multiple layers. Let us first describe these layers with the `fiona` package, which is a `geopandas` dependency.

```
import fiona
print(fiona.__name__, fiona.__version__)
for layername in fiona.listlayers('gaul2014_2015.gpkg'):
    with fiona.open('gaul2014_2015.gpkg', layer=layername) as src:
        print(layername, len(src))
```

```
fiona 1.9.5
level2 38258
level1 3422
level0 277
```

- The `level0` layer contains the country geometries defined in GAUL.
- Here, we make a map at the `level1`.
- Still, we need to load the administrative `level2` because the `Admin Units` column may refer to Admin 2 levels without mentionning the corresponding Admin 1 level.
- Given the high size the admin 2 layer, we filter the data about Japan and overwrite our geodataframe variable to save memory.

```
gaul_adm2 = gpd.read_file ('gaul2014_2015.gpkg', layer='level2')
gaul_adm2 = gaul_adm2[gaul_adm2['ADM0_NAME'] == 'Japan']
gaul_adm2.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
Index: 3348 entries, 23205 to 26552
Data columns (total 13 columns):
 #   Column      Non-Null Count  Dtype
```

```
 ---  ------       --------------  -----
  0   ADM2_CODE    3348 non-null   int64
  1   ADM2_NAME    3348 non-null   object
  2   STR2_YEAR    3348 non-null   int64
  3   EXP2_YEAR    3348 non-null   int64
  4   ADM1_CODE    3348 non-null   int64
  5   ADM1_NAME    3348 non-null   object
  6   STATUS       3348 non-null   object
  7   DISP_AREA    3348 non-null   object
  8   ADM0_CODE    3348 non-null   int64
  9   ADM0_NAME    3348 non-null   object
  10  Shape_Leng   3348 non-null   float64
  11  Shape_Area   3348 non-null   float64
  12  geometry     3348 non-null   geometry
dtypes: float64(2), geometry(1), int64(5), object(5)
memory usage: 366.2+ KB
```

The Admin 2 geodataframe has 12 columns describing the 3348 level 2 administrative units in Japan.

Filter EM-DAT Data

```
df_jpn = df[
    (df['ISO'] == 'JPN') &
    (df['Disaster Type'] == 'Earthquake') &
    (df['Start Year'] < 2024)
][['DisNo.', 'Admin Units']]
df_jpn
```

	DisNo.	Admin Units
392	2000-0428-JPN	[{"adm2_code":36308,"adm2_name":"Koodusimamura...
610	2000-0656-JPN	[{"adm1_code":1680,"adm1_name":"Okayama"},{"ad...
1013	2001-0123-JPN	[{"adm1_code":1654,"adm1_name":"Ehime"},{"adm1...
2791	2003-0249-JPN	[{"adm1_code":1652,"adm1_name":"Akita"},{"adm1...

	DisNo.	Admin Units
2884	2003-0354-JPN	[{"adm2_code":35135,"adm2_name":"Hurukawasi"},...
3014	2003-0476-JPN	[{"adm1_code":1661,"adm1_name":"Hokkaidoo"}]
3824	2004-0532-JPN	[{"adm1_code":1690,"adm1_name":"Tookyoo"},{"ad...
4182	2005-0129-JPN	[{"adm1_code":1656,"adm1_name":"Hukuoka"}]
4253	2005-0211-JPN	[{"adm1_code":1656,"adm1_name":"Hukuoka"},{"ad...
5769	2007-0101-JPN	[{"adm1_code":1678,"adm1_name":"Niigata"},{"ad...
5912	2007-0258-JPN	[{"adm1_code":1675,"adm1_name":"Nagano"},{"adm...
6311	2007-0654-JPN	[{"adm1_code":1672,"adm1_name":"Mie"},{"adm1_c...
6606	2008-0242-JPN	[{"adm1_code":1652,"adm1_name":"Akita"},{"adm2...
6637	2008-0275-JPN	[{"adm2_code":33543,"adm2_name":"Hatinohesi"}]
7335	2009-0320-JPN	[{"adm1_code":1690,"adm1_name":"Tookyoo"},{"ad...
8403	2011-0082-JPN	[{"adm1_code":1652,"adm1_name":"Akita"},{"adm1...
8447	2011-0130-JPN	[{"adm1_code":1695,"adm1_name":"Yamagata"},{"a...
9596	2013-0127-JPN	[{"adm1_code":1662,"adm1_name":"Hyoogo"}]
10468	2014-0465-JPN	[{"adm2_code":35261,"adm2_name":"Hakubamura"}]
11276	2016-0107-JPN	[{"adm1_code":1670,"adm1_name":"Kumamoto"}]
11291	2016-0121-JPN	[{"adm1_code":1670,"adm1_name":"Kumamoto"},{"a...
11631	2016-0492-JPN	[{"adm2_code":36364,"adm2_name":"Kurayosisi"}]
12449	2018-0183-JPN	[{"adm1_code":1662,"adm1_name":"Hyoogo"},{"adm...
12589	2018-0330-JPN	[{"adm2_code":34179,"adm2_name":"Atumatyoo"},{...
13030	2019-0322-JPN	[{"adm1_code":1664,"adm1_name":"Isikawa"},{"ad...
13949	2021-0105-JPN	[{"adm2_code":33868,"adm2_name":"Namiemati"}]
14005	2021-0194-JPN	[{"adm1_code":1651,"adm1_name":"Aiti"},{"adm1_...

	DisNo.	Admin Units
14584	2022-0153-JPN	NaN
15236	2023-0279-JPN	NaN

Note: The last two events were not geolocated at a higher administrative levels.

Convert Admin 2 units to Admin 1 units

We create a python function, `json_to_amdmin1` , to extract the administrative level 1 codes from the `Admin Units` column of EM-DAT, based on the `ADM1_CODE` and `ADM2_CODE` of the Japan geodataframe.

```
import json

def json_to_admin1(json_str, gdf):
    """
    Convert a JSON string to a set of administrative level 1 codes.

    Parameters
    ----------
    json_str
        A JSON string representing administrative areas, or None.
    gdf
        A GeoDataFrame containing administrative codes and their co
        levels.

    Returns
    -------
    A set of administrative level 1 (ADM1) codes extracted from the

    Raises
    ------
    ValueError
        If the administrative code is missing from the input data o
        not found in the provided GeoDataFrame.

    """
```

```
    adm_list = json.loads(json_str) if isinstance(json_str, str) el
    adm1_list = []
    if adm_list is not None:
        for entry in adm_list:
            if 'adm1_code' in entry.keys():
                adm1_code = entry['adm1_code']
            elif 'adm2_code' in entry.keys():
                gdf_sel = gdf[gdf['ADM2_CODE'] == entry['adm2_code'
                if not gdf_sel.empty:
                    adm1_code = gdf_sel.iloc[0]['ADM1_CODE']
                else:
                    raise ValueError(
                        'ADM2_CODE not found in the provided GeoDat
                    )
            else:
                raise ValueError(
                    'Administrative code is missing from the provid
                )
            adm1_list.append(adm1_code)
    return set(adm1_list)
```

We apply the function to all elements of the `Admin Units` column.

```
df_jpn.loc[:, 'Admin_1'] = df_jpn['Admin Units'].apply(
    lambda x: json_to_admin1(x, gaul_adm2))

df_jpn[['Admin Units', 'Admin_1']]
```

	Admin Units	Admin_1
392	[{"adm2_code":36308,"adm2_name":"Koodusimamura...	{1690}
610	[{"adm1_code":1680,"adm1_name":"Okayama"},{"ad...	{1680, 1691, 1686}
1013	[{"adm1_code":1654,"adm1_name":"Ehime"},{"adm1...	{1660, 1654}
2791	[{"adm1_code":1652,"adm1_name":"Akita"},{"adm1...	{1665, 1673, 1652, 1653, 1695}

	Admin Units	Admin_1
2884	[{"adm2_code":35135,"adm2_name":"Hurukawasi"},...	{1673}
3014	[{"adm1_code":1661,"adm1_name":"Hokkaidoo"}]	{1661}
3824	[{"adm1_code":1690,"adm1_name":"Tookyoo"},{"ad...	{1690, 1678}
4182	[{"adm1_code":1656,"adm1_name":"Hukuoka"}]	{1656}
4253	[{"adm1_code":1656,"adm1_name":"Hukuoka"},{"ad...	{1656, 1683}
5769	[{"adm1_code":1678,"adm1_name":"Niigata"},{"ad...	{1664, 1692, 1678}
5912	[{"adm1_code":1675,"adm1_name":"Nagano"},{"adm...	{1675, 1692, 1678}
6311	[{"adm1_code":1672,"adm1_name":"Mie"},{"adm1_c...	{1672, 1677, 1685}
6606	[{"adm1_code":1652,"adm1_name":"Akita"},{"adm2...	{1665, 1673, 1652}
6637	[{"adm2_code":33543,"adm2_name":"Hatinohesi"}]	{1653}
7335	[{"adm1_code":1690,"adm1_name":"Tookyoo"},{"ad...	{1690, 1687}
8403	[{"adm1_code":1652,"adm1_name":"Akita"},{"adm1...	{1665, 1668, 1693, 1673, 1675, 1695, 1652, 165...
8447	[{"adm1_code":1695,"adm1_name":"Yamagata"},{"a...	{1673, 1695}
9596	[{"adm1_code":1662,"adm1_name":"Hyoogo"}]	{1662}
10468	[{"adm2_code":35261,"adm2_name":"Hakubamura"}]	{1675}
11276	[{"adm1_code":1670,"adm1_name":"Kumamoto"}]	{1670}
11291	[{"adm1_code":1670,"adm1_name":"Kumamoto"},{"a...	{1674, 1683, 1670}
11631	[{"adm2_code":36364,"adm2_name":"Kurayosisi"}]	{1691}
12449	[{"adm1_code":1662,"adm1_name":"Hyoogo"},{"adm...	{1682, 1677, 1662, 1671}
12589	[{"adm2_code":34179,"adm2_name":"Atumatyoo"},{...	{1661}
13030	[{"adm1_code":1664,"adm1_name":"Isikawa"},{"ad...	{1664, 1673, 1678, 1695}
13949	[{"adm2_code":33868,"adm2_name":"Namiemati"}]	{1657}

	Admin Units	Admin_1
14005	[{"adm1_code":1651,"adm1_name":"Aiti"},{"adm1_...	{1664, 1665, 1668, 1671, 1672, 1673, 1675, 167...
14584	NaN	{}
15236	NaN	{}

Count Earthquakes per Admin 1 Units

The can be done applying the `explode` method on the new `Admin_1` column. The method will add rows based on the number of Admin 1 we have in each set inside the `Admin_1` column. Then the counting can be performed using the former `groupby` approach.

```
count_per_adm1 = df_jpn.explode('Admin_1').groupby(
    'Admin_1')['DisNo.'].count().rename('EQ Count')
count_per_adm1.head()
```

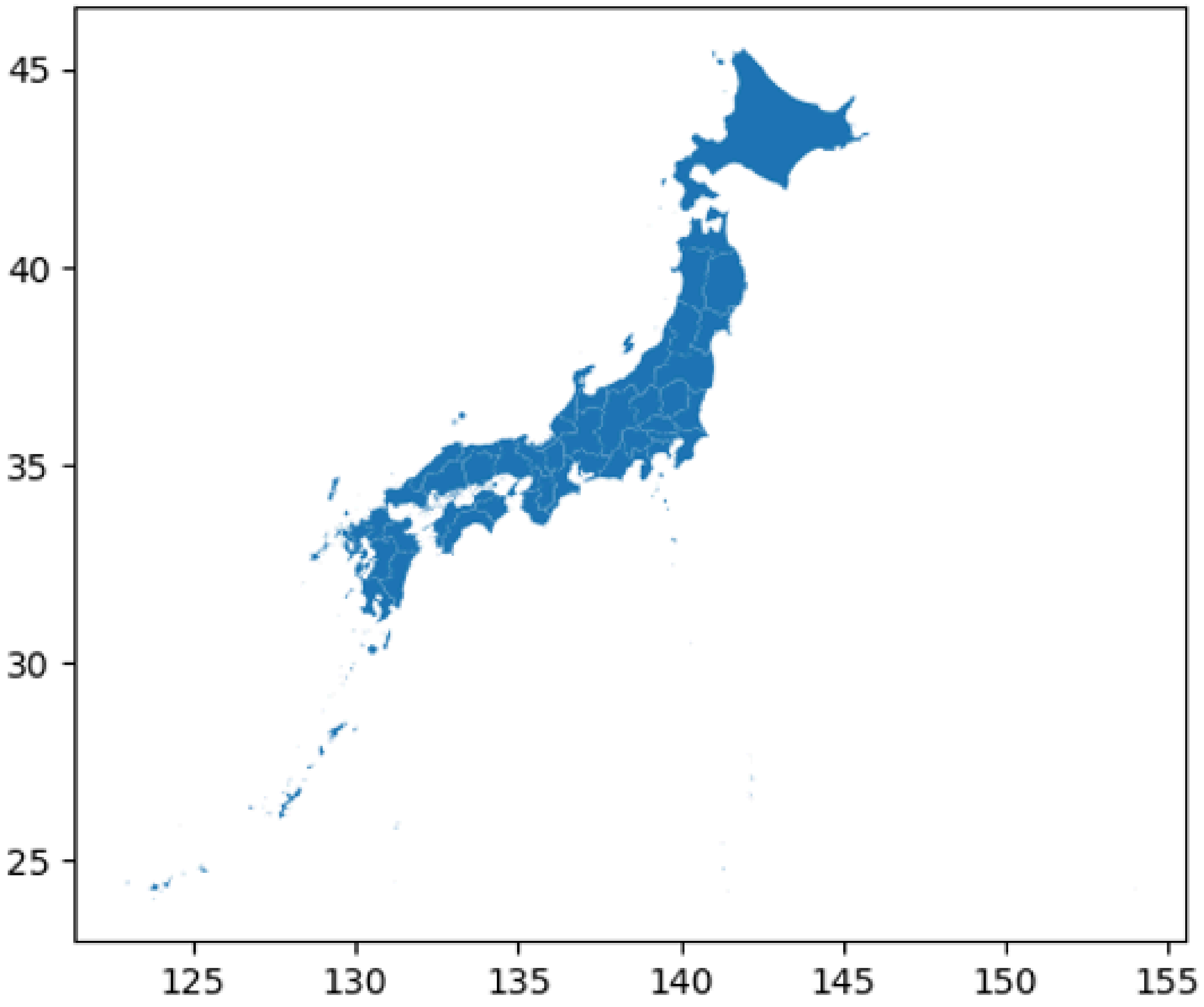
```
Admin_1
1651    1
1652    4
1653    4
1654    1
1655    1
Name: EQ Count, dtype: int64
```

Recreate the Admin 1 Layer

Since the Japan geodataframe contains the admin2 geometries, we could load the Admin 1 layer or simply dissolve the geometries based on the `ADM1_CODE` column. The `geopandas` package is equipped with the `dissolve` method.

```
gdf_jpn_adm1 = gaul_adm2.dissolve(by='ADM1_CODE')
gdf_jpn_adm1.plot()
```

```
<Axes: >
```



Output plot

Join the Two Datasets

Again, we can use the `merge` method to join the datasets together, here, based on their index.

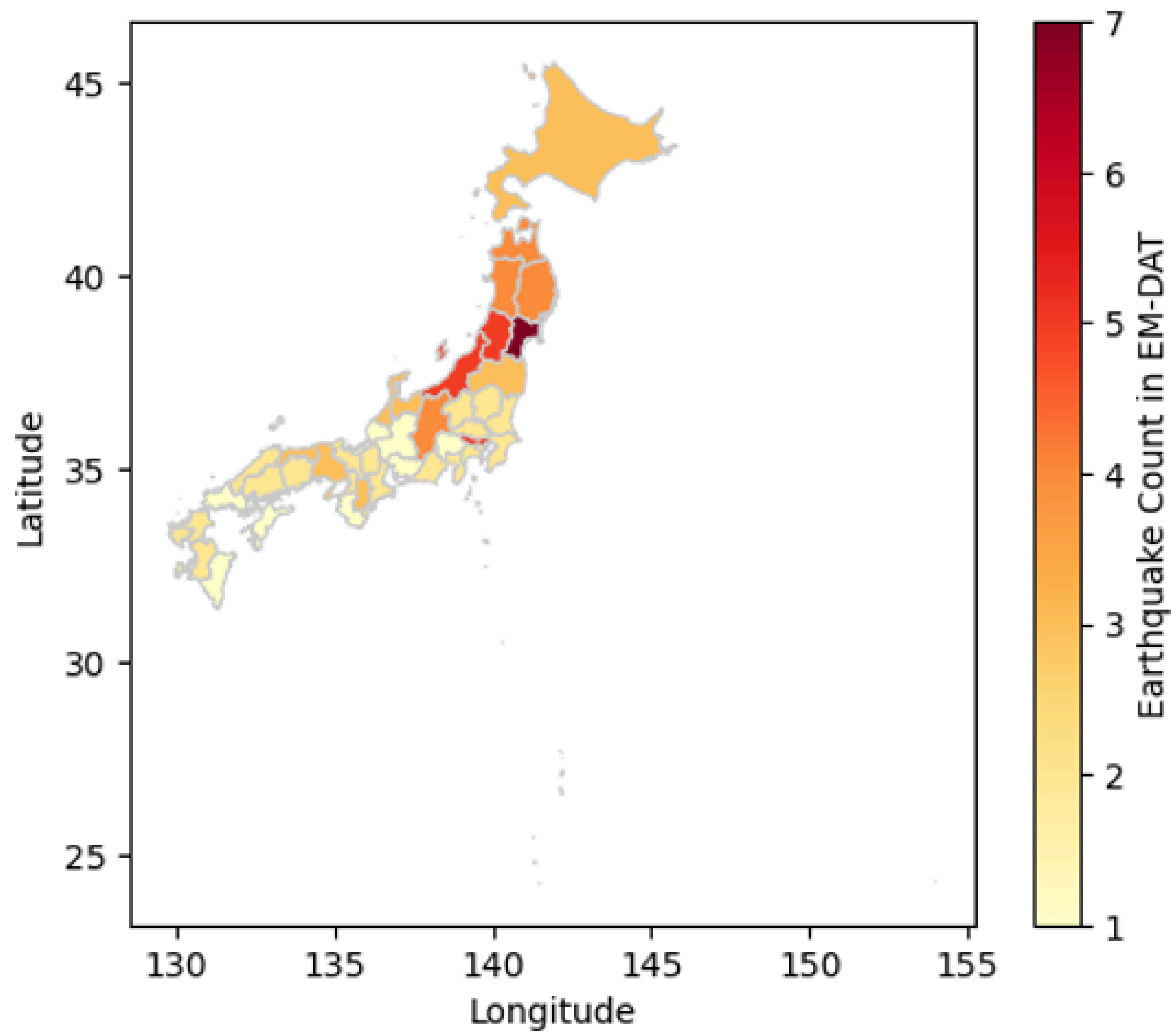
```
gdf_jpn_adm1_merged = gdf_jpn_adm1.merge(count_per_adm1,
```

```
                                    left_index=True,
                                    right_index=True,
                                    how='outer')
```

Make the Map

```
fig, ax = plt.subplots()

gdf_jpn_adm1_merged.plot(
    column='EQ Count', cmap='YlOrRd',
    linewidth=0.8, ax=ax,edgecolor='0.8',
    legend=True,
    legend_kwds={'label': "Earthquake Count in EM-DAT"}
)
_ = ax.set_xlabel('Longitude')
_ = ax.set_ylabel('Latitude')
```



Output plot

We have just covered the basics on how to join the EM-DAT `pandas` `DataFrame` with a `geopandas` `GeoDataFrame` to make maps. To delve further into your analyses, we encourage you to continue your learning of `geopandas`, `matplotlib`, or, in particular, `cartopy` for more advanced map customization, with the many resources available online.