

```
In [103]: import pandas as pd
```

1 - Read in the data into a pandas dataframe.

- The first 4 rows of our dataframe is empty, so we don not consider them.

```
In [104]: df = pd.read_csv("API_EG.USE.PCAP.KG.OE_DS2_en_csv_v2_4028587.csv", skip
```

2 - Display the usual basic information (datatypes, names, non-null values for columns) about the dataframe.

- All values relate to year's columns are in float type and reperesent the energy consumption for each country on that year.
- All series equal or greater than 2016 don not have any values.
- the 4 first column of data frame represent '**Country Name**', '**Country Code**', '**Indicator Name**', and '**Indicator Code**' and contain strings in them(object type).

```
In [105]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 266 entries, 0 to 265
Data columns (total 67 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Country Name          266 non-null   object
1   Country Code          266 non-null   object
2   Indicator Name        266 non-null   object
3   Indicator Code        266 non-null   object
4   1960                  31 non-null    float64
5   1961                  31 non-null    float64
6   1962                  31 non-null    float64
7   1963                  31 non-null    float64
8   1964                  31 non-null    float64
9   1965                  32 non-null    float64
10  1966                  32 non-null    float64
11  1967                  32 non-null    float64
12  1968                  32 non-null    float64
13  1969                  32 non-null    float64
14  1970                  32 non-null    float64
15  1971                  151 non-null   float64
16  1972                  151 non-null   float64
17  1973                  151 non-null   float64
18  1974                  151 non-null   float64
```

| | | | |
|----|-------------|--------------|---------|
| 19 | 1975 | 151 non-null | float64 |
| 20 | 1976 | 151 non-null | float64 |
| 21 | 1977 | 151 non-null | float64 |
| 22 | 1978 | 151 non-null | float64 |
| 23 | 1979 | 151 non-null | float64 |
| 24 | 1980 | 151 non-null | float64 |
| 25 | 1981 | 152 non-null | float64 |
| 26 | 1982 | 152 non-null | float64 |
| 27 | 1983 | 152 non-null | float64 |
| 28 | 1984 | 152 non-null | float64 |
| 29 | 1985 | 153 non-null | float64 |
| 30 | 1986 | 153 non-null | float64 |
| 31 | 1987 | 153 non-null | float64 |
| 32 | 1988 | 153 non-null | float64 |
| 33 | 1989 | 153 non-null | float64 |
| 34 | 1990 | 207 non-null | float64 |
| 35 | 1991 | 177 non-null | float64 |
| 36 | 1992 | 177 non-null | float64 |
| 37 | 1993 | 177 non-null | float64 |
| 38 | 1994 | 177 non-null | float64 |
| 39 | 1995 | 179 non-null | float64 |
| 40 | 1996 | 179 non-null | float64 |
| 41 | 1997 | 179 non-null | float64 |
| 42 | 1998 | 179 non-null | float64 |
| 43 | 1999 | 179 non-null | float64 |
| 44 | 2000 | 184 non-null | float64 |
| 45 | 2001 | 184 non-null | float64 |
| 46 | 2002 | 184 non-null | float64 |
| 47 | 2003 | 184 non-null | float64 |
| 48 | 2004 | 217 non-null | float64 |
| 49 | 2005 | 218 non-null | float64 |
| 50 | 2006 | 218 non-null | float64 |
| 51 | 2007 | 218 non-null | float64 |
| 52 | 2008 | 185 non-null | float64 |
| 53 | 2009 | 185 non-null | float64 |
| 54 | 2010 | 185 non-null | float64 |
| 55 | 2011 | 185 non-null | float64 |
| 56 | 2012 | 186 non-null | float64 |
| 57 | 2013 | 186 non-null | float64 |
| 58 | 2014 | 179 non-null | float64 |
| 59 | 2015 | 40 non-null | float64 |
| 60 | 2016 | 0 non-null | float64 |
| 61 | 2017 | 0 non-null | float64 |
| 62 | 2018 | 0 non-null | float64 |
| 63 | 2019 | 0 non-null | float64 |
| 64 | 2020 | 0 non-null | float64 |
| 65 | 2021 | 0 non-null | float64 |
| 66 | Unnamed: 66 | 0 non-null | float64 |

dtypes: float64(63), object(4)
memory usage: 139.4+ KB

3 - Display the dataframe.

- To show all columns of dataframe you can do as below.

```
In [106]: pd.set_option("display.max_columns",67)
```

```
In [107]: df
```

```
Out[107]:
```

| | Country Name | Country Code | Indicator Name | Indicator Code | 1960 | 1961 | 1962 | 1963 | 1964 | 1965 |
|-----|-----------------------------|--------------|--|-------------------|------|------|------|------|------|------|
| 0 | Aruba | ABW | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 1 | Africa Eastern and Southern | AFE | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 2 | Afghanistan | AFG | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 3 | Africa Western and Central | AFW | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 4 | Angola | AGO | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 261 | Kosovo | XKX | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| | | | Energy | | | | | | | |

| | | | | | | | | | | |
|-----|--------------|-----|--|-------------------|-----|-----|-----|-----|-----|-----|
| 262 | Yemen, Rep. | YEM | use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 263 | South Africa | ZAF | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 264 | Zambia | ZMB | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 265 | Zimbabwe | ZWE | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |

266 rows × 67 columns

4 - Find out what values occur under "Indicator Name".

- There is only one unique value under this column.

```
In [108]: df["Indicator Name"]
```

```
Out[108]: 0    Energy use (kg of oil equivalent per capita)
1    Energy use (kg of oil equivalent per capita)
2    Energy use (kg of oil equivalent per capita)
3    Energy use (kg of oil equivalent per capita)
4    Energy use (kg of oil equivalent per capita)
...
261  Energy use (kg of oil equivalent per capita)
262  Energy use (kg of oil equivalent per capita)
263  Energy use (kg of oil equivalent per capita)
264  Energy use (kg of oil equivalent per capita)
265  Energy use (kg of oil equivalent per capita)
Name: Indicator Name, Length: 266, dtype: object
```

- The value under the "Indicator Name" column is : "**Energy use (kg of oil equivalent per capita)**"

```
In [109]: df["Indicator Name"].unique()
```

```
Out[109]: array(['Energy use (kg of oil equivalent per capita)'], dtype=object)
```

5 - Set the name of the columns to the only value you found under "Indicator Name" (the columns and their labels remain the same!). (Apply the operation to your dataframe!)

- First we extract the unique value under the "Indicator Name" column.
- Then we set name of column to this value.

```
In [110]: df.rename_axis(df["Indicator Name"].unique(), axis=1, inplace=True)
df
```

```
Out[110]:
```

| | Energy use (kg of oil equivalent per capita) | Country Name | Country Code | Indicator Name | Indicator Code | 1960 | 1961 | 1962 | 1963 | 1964 |
|---|--|-----------------------------|--------------|--|-------------------|------|------|------|------|------|
| 0 | | Aruba | ABW | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN |
| 1 | | Africa Eastern and Southern | AFE | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN |
| 2 | | Afghanistan | AFG | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN |
| 3 | | Africa Western and Central | AFW | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN |
| 4 | | Angola | AGO | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN |

| | | | | | | | | | | |
|-----|--------------|-----|--|-------------------|-----|-----|-----|-----|-----|-----|
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 261 | Kosovo | XKX | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 262 | Yemen, Rep. | YEM | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 263 | South Africa | ZAF | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 264 | Zambia | ZMB | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |
| 265 | Zimbabwe | ZWE | Energy use (kg of oil equivalent per capita) | EG.USE.PCAP.KG.OE | NaN | NaN | NaN | NaN | NaN | NaN |

266 rows × 67 columns

6 - Create a new dataframe *dfcode* which contains the "Country Code" and "Country Name" columns of your original dataframe. You will continue working with your original dataframe, in what follows, though.

```
In [111]: dfcode=df[["Country Code" , "Country Name"]]
dfcode
```

```
Out[111]:
```

| | Energy use (kg of oil equivalent per capita) | Country Code | Country Name |
|-----|--|--------------|-----------------------------|
| 0 | | ABW | Aruba |
| 1 | | AFE | Africa Eastern and Southern |
| 2 | | AFG | Afghanistan |
| 3 | | AFW | Africa Western and Central |
| 4 | | AGO | Angola |
| ... | | ... | ... |
| 261 | | XKX | Kosovo |
| 262 | | YEM | Yemen, Rep. |
| 263 | | ZAF | South Africa |
| 264 | | ZMB | Zambia |
| 265 | | ZWE | Zimbabwe |

266 rows × 2 columns

7 - Remove the "Country Code", "Indicator Name", "Indicator Code" columns. (Apply the operation to your dataframe!)

- we created a dataframe named dfcode with two columns : "Country Code" and "Country Name" in step 6. Thus we can delete "Country Code" from our original dataframe, because we can access them through the common column of 'df' and 'dfcode', "Country Name"
- On the other hand, both the "Indicator Code" and "Indicator Name" columns have values that are unique for them.
- We set the name of columns to **"Energy use (kg of oil equivalent per capita)"** in step 5. Then it seems reasonable to delete these two columns from our dataframe as well.

```
In [112]: df.drop(columns=["Country Code", "Indicator Name", "Indicator Code"]
df
```

Out[112]:

| | Energy use (kg of oil equivalent per capita) | Country Name | 1960 | 1961 | 1962 | 1963 | 1964 | 1965 | 1966 | 1967 | 1968 | 1969 | 1970 | |
|-----|---|--------------------------------------|------|------|------|------|------|------|------|------|------|------|------|----|
| 0 | | Aruba | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| 1 | | Africa Eastern and Southern | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 7 |
| 2 | | Afghanistan | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| 3 | | Africa Western and Central | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 8 |
| 4 | | Angola | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 6 |
| ... | | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | |
| 261 | | Kosovo | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | |
| 262 | | Yemen, Rep. | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 1 |
| 263 | | South Africa | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 20 |
| 264 | | Zambia | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 8 |
| 265 | | Zimbabwe | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 9 |

266 rows × 64 columns

8 - Make the column "Country Name" the index of your dataframe. (Apply the operation to your dataframe!)

- Values under the column "Country Name" are unique, then we can set them as our indexes in the dataframe.


```
In [115]: df.set_index("Country Name", inplace = True)
df
```

```
Out[115]:
```

| Energy use (kg of oil equivalent per capita) | 1960 | 1961 | 1962 | 1963 | 1964 | 1965 | 1966 | 1967 | 1968 | 1969 | 1970 | 1971 |
|---|------|------|------|------|------|------|------|------|------|------|------|-------------|
| Country Name | | | | | | | | | | | | |
| Aruba | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Africa Eastern and Southern | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 787.535043 |
| Afghanistan | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Africa Western and Central | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 511.982019 |
| Angola | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 637.410306 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| Kosovo | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Yemen, Rep. | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 116.893021 |
| South Africa | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 2004.341886 |
| Zambia | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 835.864574 |
| Zimbabwe | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 993.124493 |

266 rows × 63 columns

9 - Get rid of columns which contain no values. (Apply the operation to your dataframe!)

- There are some columns which have no values, so we can ignore them.
- These columns are : columns from 2016 to the end.

```
In [116]: df.dropna(axis=1, how="all", inplace = True)
df
```

```
Out[116]:
```

| Energy use (kg of oil equivalent per capita) | 1960 | 1961 | 1962 | 1963 | 1964 | 1965 | 1966 | 1967 | 1968 | 1969 | 1970 | 1971 |
|---|------|------|------|------|------|------|------|------|------|------|------|-------------|
| Country Name | | | | | | | | | | | | |
| Aruba | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Africa Eastern and Southern | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 787.535043 |
| Afghanistan | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Africa Western and Central | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 511.982019 |
| Angola | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 637.410306 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| Kosovo | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Yemen, Rep. | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 116.893021 |
| South Africa | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 2004.341886 |
| Zambia | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 835.864574 |
| Zimbabwe | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 993.124493 |

266 rows × 56 columns

10 - Display the basic statistics by year, incl. minimal, maximal, mean, median, standard deviation values. (Make sure you display these values for all the years!)

In [118]: `df.describe()`

Out[118]:

| Energy use (kg of oil equivalent per capita) | 1960 | 1961 | 1962 | 1963 | 1964 | 1965 |
|---|--------------|--------------|--------------|--------------|--------------|--------------|
| count | 31.000000 | 31.000000 | 31.000000 | 31.000000 | 31.000000 | 32.000000 |
| mean | 2385.557701 | 2420.522343 | 2521.248064 | 2656.031388 | 2764.165888 | 2808.617510 |
| std | 1997.388654 | 1981.575639 | 1971.311855 | 1992.182413 | 2089.070745 | 2058.798654 |
| min | 289.057068 | 322.490578 | 350.101258 | 367.811430 | 410.251827 | 440.882930 |
| 25% | 1401.298789 | 1455.073445 | 1568.387025 | 1725.539544 | 1791.042783 | 1740.689130 |
| 50% | 1906.174930 | 1937.644745 | 2081.011621 | 2268.427890 | 2341.146313 | 2435.746810 |
| 75% | 2787.029421 | 2824.192050 | 2943.750064 | 3104.157719 | 3224.790698 | 3324.413800 |
| max | 10523.406695 | 10534.018211 | 10414.540920 | 10465.813021 | 11150.050343 | 10926.395170 |

11 - What can you conclude from the yearly descriptives? Answer in a markdown cell.

- The row "**count**" shows the number of cells with values in each year. Here, these values are energy use. For example, it is clear that between 1960 to 1964 we have only 31 values for energy consumption for countries.
- "**mean**" shows the average of the energy consumption of all countries in each year.
- "**std**" shows the standard deviation of the energy consumption of all countries in each year.
- The rows "**min**" and "**max**" indicate the minimum and maximum energy consumption of all countries in each year.
- The distances between
 - "**min**" and "**25%**",
 - "**25%**" and "**50%**",
 - "**50%**" and "**75%**",
 - "**75%**" and "**max**" indicate the first to fourth quartiles of data(energy usage), respectively.
- "**50%**" shows the median of the energy consumption of all countries in each year. By comparing the value of this row by the mean's row we can conclude that our data on that year is left or right skewed. For instance, in our dataframe all energy consumption of all countries in each year are right skewed.

12 - Display the basic statistics by country, incl. minimal, maximal, mean, median, standard deviation values. (Make sure you display these values for all the countries!)

- The function `basic_statistics` get a serie as an input and returns the basic statistics of it.
- By applying this function to the dataframe while setting the `axis=1` we will have basic statistics for each country.

```
In [119]: def basic_statistics(serie):
            return serie.describe()
basic_stat = df.apply(basic_statistics, axis=1)
basic_stat
```

```
Out[119]:
```

| | count | mean | std | min | 25% | 50% | 75% |
|------------------------------------|-------|-------------|------------|-------------|-------------|-------------|-----------|
| Country Name | | | | | | | |
| Aruba | 0.0 | NaN | NaN | NaN | NaN | NaN | NaN |
| Africa Eastern and Southern | 44.0 | 774.382105 | 33.741279 | 725.668196 | 747.688295 | 771.573635 | 789.4547 |
| Afghanistan | 0.0 | NaN | NaN | NaN | NaN | NaN | NaN |
| Africa Western and Central | 44.0 | 569.449117 | 23.837452 | 511.982019 | 560.362458 | 569.460212 | 580.0802 |
| Angola | 44.0 | 507.655185 | 57.699718 | 433.572486 | 466.935088 | 491.890571 | 536.4730 |
| ... | ... | ... | ... | ... | ... | ... | ... |
| Kosovo | 15.0 | 1216.102185 | 133.739458 | 908.608824 | 1142.072713 | 1179.568641 | 1303.5480 |
| Yemen, Rep. | 43.0 | 223.657474 | 75.290318 | 90.216323 | 166.481024 | 221.497822 | 277.1749 |
| South Africa | 44.0 | 2486.783900 | 238.607050 | 1984.178909 | 2360.769433 | 2511.510478 | 2680.4802 |
| Zambia | 43.0 | 697.211345 | 92.585850 | 599.104868 | 615.968344 | 672.573813 | 771.0986 |
| Zimbabwe | 43.0 | 857.661556 | 66.749616 | 724.292388 | 822.144282 | 851.163079 | 893.3659 |

266 rows × 8 columns

13 - Display the basic statistics of your previous by country-statistics (i.e., the mean of country means, etc.).

In [120]: `basic_stat.describe()`

Out[120]:

| | count | mean | std | min | 25% | 50% | |
|--------------|------------|--------------|-------------|-------------|--------------|--------------|-------|
| count | 266.000000 | 220.000000 | 219.000000 | 220.000000 | 220.000000 | 220.000000 | 220 |
| mean | 29.992481 | 1895.796955 | 456.997254 | 1105.604629 | 1617.384096 | 1894.713150 | 2200 |
| std | 20.445970 | 2368.170137 | 840.838073 | 1317.515592 | 1986.833783 | 2310.093780 | 2902 |
| min | 0.000000 | 12.400284 | 0.725879 | 9.548060 | 9.558898 | 11.760481 | 14 |
| 25% | 5.000000 | 520.734943 | 72.313997 | 333.756270 | 465.168462 | 534.788916 | 562 |
| 50% | 44.000000 | 999.663055 | 226.716363 | 538.671310 | 784.783249 | 985.088449 | 1132 |
| 75% | 44.000000 | 2513.184092 | 515.951663 | 1442.352848 | 2257.972452 | 2602.494966 | 2892 |
| max | 56.000000 | 18278.542119 | 8751.700807 | 8775.992603 | 14525.570902 | 15664.302283 | 25096 |

14 - Display the first thirty rows of your original dataframe after sorting by the values for the last year in descending order. (Do not apply sorting to your original dataframe, just display!)

- first we find the last year.
- then sort the data by the descending order
- then show only the first thirty rows.

In [121]: `year = df.columns[-1]
df.sort_values(year , ascending= False).head(30)`

Out[121]:

| | Energy use (kg of oil equivalent per capita) | 1960 | 1961 | 1962 | 1963 | 1964 | |
|--------------------------|---|--------------|--------------|--------------|--------------|----------|--|
| Country Name | | | | | | | |
| Iceland | 3082.711563 | 2916.706232 | 3028.298369 | 3279.602269 | 3306.815957 | 3444.55 | |
| Canada | 4251.435911 | 4307.820754 | 4451.560116 | 4694.120070 | 4903.607607 | 5153.93 | |
| North America | 5516.355617 | 5494.086457 | 5654.544543 | 5869.044418 | 6024.094790 | 6201.77 | |
| United States | 5641.740755 | 5612.079503 | 5774.586315 | 5986.783954 | 6136.938230 | 6307.89 | |
| Luxembourg | 10523.406695 | 10534.018211 | 10414.540920 | 10465.813021 | 11150.050343 | 10926.39 | |
| Finland | 2196.953067 | 2252.778690 | 2361.743876 | 2478.912009 | 2678.383166 | 2887.69 | |
| Norway | 1906.174930 | 1937.644745 | 2052.054484 | 2182.993108 | 2320.013134 | 2539.59 | |

| | | | | | | |
|----------------------------------|-------------|-------------|-------------|-------------|-------------|---------|
| Australia | 3063.554271 | 3115.787084 | 3172.974865 | 3284.050959 | 3349.414167 | 3463.21 |
| Korea, Rep. | NaN | NaN | NaN | NaN | NaN | |
| Sweden | 2698.792303 | 2742.123469 | 2887.236252 | 3080.414075 | 3273.508965 | 3437.54 |
| Post-demographic dividend | 2812.288505 | 2848.671622 | 2969.271547 | 3127.901363 | 3237.046840 | 3322.74 |
| Belgium | 2519.497320 | 2570.815623 | 2810.061148 | 3043.306993 | 3021.647212 | 3116.03 |
| High income | 2761.770337 | 2799.712478 | 2918.228582 | 3069.538122 | 3175.606633 | 3260.61 |
| New Zealand | 1685.788431 | 1763.259908 | 1791.461322 | 1924.229007 | 2176.168871 | 2241.41 |
| Netherlands | 1825.934253 | 1879.150201 | 2081.011621 | 2268.427890 | 2349.083542 | 2493.15 |
| Estonia | NaN | NaN | NaN | NaN | NaN | |
| OECD members | 2666.979333 | 2702.066693 | 2815.604186 | 2959.832864 | 3060.624410 | 3142.69 |
| Czech Republic | NaN | NaN | NaN | NaN | NaN | |
| Germany | 1952.588632 | 1994.324633 | 2124.848539 | 2281.289928 | 2341.146313 | 2378.33 |
| Austria | 1546.261468 | 1554.034906 | 1675.873621 | 1823.995225 | 1855.085155 | 1851.84 |
| France | 1699.250872 | 1745.201546 | 1861.042066 | 1983.465817 | 2085.161125 | 2109.85 |
| Japan | 867.203098 | 971.998193 | 1013.257624 | 1147.292732 | 1272.480553 | 1374.52 |
| Euro area | 1403.942741 | 1455.391774 | 1567.862991 | 1686.600242 | 1762.650228 | 1816.95 |
| European Union | 1487.664770 | 1541.096121 | 1653.838779 | 1764.478845 | 1840.896534 | 1885.71 |
| Slovenia | NaN | NaN | NaN | NaN | NaN | |
| Slovak Republic | NaN | NaN | NaN | NaN | NaN | |
| Switzerland | 1398.654836 | 1454.755116 | 1568.911060 | 1869.587498 | 1819.435337 | 1943.60 |
| Ireland | 1318.812487 | 1396.466152 | 1412.729677 | 1453.962105 | 1522.194973 | 1511.90 |
| Denmark | 1922.973673 | 2023.308390 | 2296.289563 | 2502.927644 | 2600.155821 | 2822.73 |
| Israel | NaN | NaN | NaN | NaN | NaN | |

15 - What are some of the conclusions you can draw from the data you displayed (e.g., about the "countries" in the data)?

- We can conclude from the output that Iceland (17478.893037) had the highest consumption in 2015 Israel (2777.875324) had the lowest energy useage in that year between the 30 first countries.
- It is clear that Iceland as the first country in the list had consumption more than twice of the second country in the list Canada. But from Canada to the end of list, the consumption is almost one third in 2015.

16 - Calculate the difference between the (0-filled) values for the years 2010 and 2000 by country, sort it in a descending order, and display the first 30 rows. What are some of the conclusions you could draw from what you see?

- While in subtraction the Nan is considered as zero, we can do the following.

```
In [122]: difference = df["2010"] - df["2000"]
difference.sort_values(ascending=False).head(30)
```

```
Out[122]: Country Name
Trinidad and Tobago      7343.881646
Iceland                  5931.617954
Oman                     2817.166090
Saudi Arabia             2028.716721
Gabon                    1931.836600
Kazakhstan               1837.648729
Caribbean small states  1773.999293
Kuwait                   1569.504601
Brunei Darussalam       1180.641360
Turkmenistan             1164.474277
Norway                   1108.512430
China                    1055.735243
Korea, Rep.              1042.816465
Gibraltar                1037.278934
Iran, Islamic Rep.       894.791886
Estonia                  848.028800
Late-demographic dividend 791.572455
East Asia & Pacific (IDA & IBRD countries) 789.415631
East Asia & Pacific (excluding high income) 778.339797
Upper middle income      721.507825
East Asia & Pacific       707.439099
Luxembourg               652.641236
Thailand                  605.452916
Middle East & North Africa 597.518172
Russian Federation       594.763584
Bosnia and Herzegovina   590.489037
Finland                  566.591674
Latvia                   530.193540
Kosovo                   496.432062
Malaysia                 493.635326
dtype: float64
```

Or we can do the above calculation as below as well:


```
In [123]: difference = df["2010"].fillna(0) - df["2000"].fillna(0)
difference.sort_values(ascending=False).head(30)
```

```
Out[123]: Country Name
Trinidad and Tobago      7343.881646
Iceland                  5931.617954
Oman                    2817.166090
Saudi Arabia            2028.716721
Gabon                   1931.836600
Montenegro              1898.288421
Kazakhstan              1837.648729
Caribbean small states 1773.999293
Kuwait                  1569.504601
Brunei Darussalam      1180.641360
Turkmenistan            1164.474277
Norway                  1108.512430
China                   1055.735243
Korea, Rep.             1042.816465
Gibraltar               1037.278934
Iran, Islamic Rep.      894.791886
Estonia                 848.028800
Late-demographic dividend 791.572455
East Asia & Pacific (IDA & IBRD countries) 789.415631
East Asia & Pacific (excluding high income) 778.339797
Upper middle income     721.507825
East Asia & Pacific      707.439099
Luxembourg              652.641236
Thailand                 605.452916
Middle East & North Africa 597.518172
Russian Federation      594.763584
Bosnia and Herzegovina  590.489037
Finland                 566.591674
Latvia                  530.193540
Kosovo                  496.432062
dtype: float64
```

Conclusion :

- As we can see Trinidad and Tobago had the highest growth rates between 2000 to 2010 in terms of energy consumption and the 30th country in this regard is Kosovo.
- All first 30 countries in the list had positive consumption growth rates from 2000 to 2010.
- However, I have to mention that in calculations of the difference between the two years, we considered the missing values as zero. Considering that the data for energy consumption is somehow a time series, it might better to execute a more proper way to filling missing values instead of fill them by zero.

17 - Display the mean values by year as a percentage of the maximal values for that year (e.g., if the mean value for 1965 were 200, and the maximal for 1965 were 400, then for 1965, you should be displaying 50).

- The "mean_as_percent" function calculates the *mean* values by year as a percentage of the *maximal* values.
- By applying the function to the dataframe this function executes on all columns of the dataframe.

```
In [124]: def mean_as_percent(column):  
           value = (column.mean()/column.max())*100  
           return value  
df.apply(mean_as_percent)
```

```
Out[124]: Energy use (kg of oil equivalent per capita)  
1960      22.669063  
1961      22.978148  
1962      24.208922  
1963      25.378166  
1964      24.790614  
1965      25.704887  
1966      27.558484  
1967      28.676396  
1968      28.423581  
1969      27.937783  
1970      29.908848  
1971       4.648137  
1972       4.854237  
1973       4.650674  
1974       4.936191  
1975       6.891470  
1976       6.512473  
1977       6.714076  
1978       7.621300  
1979       7.911123  
1980       7.606008  
1981       7.969176  
1982       7.358451  
1983       6.937944  
1984      10.107683  
1985      13.011385  
1986      13.287579  
1987      13.817290  
1988      14.030779  
1989      14.496496  
1990      14.650733  
1991      14.829843  
1992      13.987773
```

```
1993    13.492196
1994    13.526670
1995    13.459529
1996    13.153490
1997    11.766205
1998    11.653551
1999    11.285838
2000    12.071856
2001    11.602816
2002    10.760776
2003    11.293554
2004     9.663841
2005    11.080832
2006    11.429581
2007    12.166881
2008    15.145194
2009    14.119852
2010    14.430814
2011    13.533453
2012    13.845241
2013    13.285970
2014    13.778170
2015    24.189451
dtype: float64
```

18 - Display the countries (not the subdataframe, just the countries!) where the values for all years are missing.

- It is wise to have an overview of countries that have no values for all years.
- This can be done as below.

```
In [125]: Nan_values_allyears = df.isna().all(axis=1)
df.loc[Nan_values_allyears, :].index
```

```
Out[125]: Index(['Aruba', 'Afghanistan', 'Andorra', 'American Samoa', 'Burundi',
                'Burkina Faso', 'Bermuda', 'Central African Republic',
                'Channel Islands', 'Cayman Islands', 'Faroe Islands',
                'Micronesia, Fed. Sts.', 'Guinea', 'Greenland', 'Guam', 'Isle
of Man',
                'Not classified', 'Lao PDR', 'Liberia', 'Low income', 'Liechte
nstein',
                'Macao SAR, China', 'St. Martin (French part)', 'Monaco', 'Mad
agascar',
                'Mali', 'Northern Mariana Islands', 'Mauritania', 'Malawi',
                'New Caledonia', 'Nauru', 'Papua New Guinea', 'Puerto Rico',
                'West Bank and Gaza', 'French Polynesia', 'Rwanda', 'Sierra Le
one',
                'San Marino', 'Somalia', 'Sint Maarten (Dutch part)',
                'Turks and Caicos Islands', 'Chad', 'Tuvalu', 'Uganda',
                'British Virgin Islands', 'Virgin Islands (U.S.)'],
                dtype='object', name='Country Name')
```

19 - Display the subdataframe with the countries whose final year's values are bigger than the final year values' mean.

In [126]: `mask = df[df.columns[len(df.columns)-1]] > df[df.columns[len(df.columns)-1]]`
`df.loc[mask]`

Out[126]:

| Energy use (kg of oil equivalent per capita) | 1960 | 1961 | 1962 | 1963 | 1964 | |
|---|--------------|--------------|--------------|--------------|--------------|----------|
| Country Name | | | | | | |
| Australia | 3063.554271 | 3115.787084 | 3172.974865 | 3284.050959 | 3349.414167 | 3463.21 |
| Belgium | 2519.497320 | 2570.815623 | 2810.061148 | 3043.306993 | 3021.647212 | 3116.03 |
| Canada | 4251.435911 | 4307.820754 | 4451.560116 | 4694.120070 | 4903.607607 | 5153.93 |
| Finland | 2196.953067 | 2252.778690 | 2361.743876 | 2478.912009 | 2678.383166 | 2887.69 |
| High income | 2761.770337 | 2799.712478 | 2918.228582 | 3069.538122 | 3175.606633 | 3260.61 |
| Iceland | 3082.711563 | 2916.706232 | 3028.298369 | 3279.602269 | 3306.815957 | 3444.55 |
| Korea, Rep. | NaN | NaN | NaN | NaN | NaN | |
| Luxembourg | 10523.406695 | 10534.018211 | 10414.540920 | 10465.813021 | 11150.050343 | 10926.39 |
| North America | 5516.355617 | 5494.086457 | 5654.544543 | 5869.044418 | 6024.094790 | 6201.77 |
| Netherlands | 1825.934253 | 1879.150201 | 2081.011621 | 2268.427890 | 2349.083542 | 2493.15 |
| Norway | 1906.174930 | 1937.644745 | 2052.054484 | 2182.993108 | 2320.013134 | 2539.59 |
| New Zealand | 1685.788431 | 1763.259908 | 1791.461322 | 1924.229007 | 2176.168871 | 2241.41 |
| Post- demographic dividend | 2812.288505 | 2848.671622 | 2969.271547 | 3127.901363 | 3237.046840 | 3322.74 |
| Sweden | 2698.792303 | 2742.123469 | 2887.236252 | 3080.414075 | 3273.508965 | 3437.54 |
| United States | 5641.740755 | 5612.079503 | 5774.586315 | 5986.783954 | 6136.938230 | 6307.89 |

20 - Load the "capital.json" file, and arrive at a dataframe capitaldf containing the name, capital, iso2, iso3 information (these three should end up as the columns) for every country in it.

```
In [127]: capital = pd.read_json("capital.json")
capitaldf = pd.json_normalize(capital["data"])
capitaldf
```

```
Out[127]:
```

| | name | capital | iso2 | iso3 |
|-----|-------------------|-----------|------|------|
| 0 | Afghanistan | Kabul | AF | AFG |
| 1 | Aland Islands | Mariehamn | AX | ALA |
| 2 | Albania | Tirana | AL | ALB |
| 3 | Algeria | Algiers | DZ | DZA |
| 4 | American Samoa | Pago Pago | AS | ASM |
| ... | ... | ... | ... | ... |
| 246 | Wallis and Futuna | Mata Utu | WF | WLF |
| 247 | Western Sahara | El-Aaiun | EH | ESH |
| 248 | Yemen | Sanaa | YE | YEM |
| 249 | Zambia | Lusaka | ZM | ZMB |
| 250 | Zimbabwe | Harare | ZW | ZWE |

251 rows × 4 columns

21 - Find the subdataframe of the dfcode dataframe you created earlier on where the "Country Code" value is not in the "iso3" column of capitaldf. Hint: look up and use the .isin pandas Series method. Store this subdataframe in the variable dfnocode. Display dfnocode and explain in a markdown cell what you see and what this could be used for.

- **'dfnocode' containing 50 countries from 'dfcode' that their codes are not in 'iso3' column of 'capitaldf'.**
- **So if we want to add a new country to 'capitaldf' dataframe from our original dataframe, we can check it from 'dfnocode' whether that country is already in the 'capitaldf' or not.**

```
In [128]: filt = dfcode["Country Code"].isin(capitaldf["iso3"])
dfnocode = dfcode.loc[~filt]
dfnocode
```

```
Out[128]:
```

| | Energy use (kg of oil equivalent per capita) | Country Code | Country Name |
|--|--|--------------|--------------|
|--|--|--------------|--------------|

| | | |
|------------|------------|--|
| 1 | AFE | Africa Eastern and Southern |
| 3 | AFW | Africa Western and Central |
| 7 | ARB | Arab World |
| 36 | CEB | Central Europe and the Baltics |
| 38 | CHI | Channel Islands |
| 49 | CSS | Caribbean small states |
| 61 | EAP | East Asia & Pacific (excluding high income) |
| 62 | EAR | Early-demographic dividend |
| 63 | EAS | East Asia & Pacific |
| 64 | ECA | Europe & Central Asia (excluding high income) |
| 65 | ECS | Europe & Central Asia |
| 68 | EMU | Euro area |
| 73 | EUU | European Union |
| 74 | FCS | Fragile and conflict affected situations |
| 95 | HIC | High income |
| 98 | HPC | Heavily indebted poor countries (HIPC) |
| 102 | IBD | IBRD only |
| 103 | IBT | IDA & IBRD total |
| 104 | IDA | IDA total |
| 105 | IDB | IDA blend |
| 107 | IDX | IDA only |
| 110 | INX | Not classified |
| 128 | LAC | Latin America & Caribbean (excluding high income) |
| 134 | LCN | Latin America & Caribbean |
| 135 | LDC | Least developed countries: UN classification |
| 136 | LIC | Low income |
| 139 | LMC | Lower middle income |
| 140 | LMY | Low & middle income |
| 142 | LTE | Late-demographic dividend |
| 153 | MEA | Middle East & North Africa |
| 156 | MIC | Middle income |

| | | |
|-----|-----|---|
| 161 | MNA | Middle East & North Africa (excluding high inc... |
| 170 | NAC | North America |
| 181 | OED | OECD members |
| 183 | OSS | Other small states |
| 191 | PRE | Pre-demographic dividend |
| 197 | PSS | Pacific island small states |
| 198 | PST | Post-demographic dividend |
| 204 | SAS | South Asia |
| 215 | SSA | Sub-Saharan Africa (excluding high income) |
| 217 | SSF | Sub-Saharan Africa |
| 218 | SST | Small states |
| 230 | TEA | East Asia & Pacific (IDA & IBRD countries) |
| 231 | TEC | Europe & Central Asia (IDA & IBRD countries) |
| 236 | TLA | Latin America & the Caribbean (IDA & IBRD coun... |
| 238 | TMN | Middle East & North Africa (IDA & IBRD countries) |
| 240 | TSA | South Asia (IDA & IBRD) |
| 241 | TSS | Sub-Saharan Africa (IDA & IBRD countries) |
| 249 | UMC | Upper middle income |
| 259 | WLD | World |

In [129]: `len(dfnocode)`

Out[129]: 50

22 - Now display the subdataframe of your main dataframe with the yearly data where the index (the Country Name) is not in the "Country Name" column of dfnocode.


```
In [130]: condition = df.index.isin(dfnocode["Country Name"])
df.loc[~condition]
```

```
Out[130]:
```

| Energy use (kg of oil equivalent per capita) | 1960 | 1961 | 1962 | 1963 | 1964 | 1965 | 1966 | 1967 | 1968 | 1969 | 1970 | 1971 |
|---|------|------|------|------|------|------|------|------|------|------|------|-------------|
| Country Name | | | | | | | | | | | | |
| Aruba | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Afghanistan | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Angola | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 637.410306 |
| Albania | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 785.161526 |
| Andorra | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| Kosovo | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| Yemen, Rep. | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 116.893021 |
| South Africa | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 2004.341886 |
| Zambia | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 835.864574 |
| Zimbabwe | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | 993.124493 |

216 rows × 56 columns

```
In [ ]:
```