# **Assignment 2 - Pandas**

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## The Story

Use Markdown cells to write a brief summary of the data analysis you are planning to undertake:

- · What is the goal of this work?
- · What kind of data is analyzed in this work?
- · What summary statistics are obtained in this work?

This part is worth 3 marks. I recommend writing this part once you have completed all the remaining parts of this assignment.

#### Brief introduction and objective of the analysis

- 1. Constructed 2 dataframes using World Bank data.
- 2. The first DataFrame: 'dataframe 1' describes the Economy of the selected countries.
- 3. The second DataFrame: 'dataframe\_2' describes the Energy consumption of the countries, access to electricity, how electricity is produced (fossil, renewable).
- 4. The goal was to identify which factors has the most correlation with renewable energy usage or shifts towards it.

Please note: that initially a few extra indicators were chosen to get a feel of the economy and the energy consumption but all of them weren't used in the analysis.

The data analysed was numeric, structured with proper labels.

#### **Summary**

No correlation was found between strength or size of an economy and the dependency on renewable sources fro electricity generation.

France and Canada are utilising green sources the most from my country list and Europeean countries have more inclination towards renewable energy.

## **Data Preparation**

#### Countries

```
In [1]: # Codes for the chosen countries
        country codes = ["CAN", "CHN", "DEU", "EGY", "FRA", "GBR", "IND", "JPN", "NGA", "USA", "ZAF"]
In [2]: # Creating a dictionary in the country code:country name format:
        # Step 1: Creating a list of country names in the same order as the country codes list
        country proper names = ['Canada', 'China', 'Egypt', 'France', 'Germany', 'India', 'Japan', 'Nigeria',
                                 'South Africa', 'United Kingdom', 'United States']
        country names = {}
        for i in range(0,len(country codes)):
            country names[country codes[i]] = country proper names[i]
        # The final dictionary
        country names
Out[2]: {'CAN': 'Canada',
          'CHN': 'China',
         'DEU': 'Egypt',
         'EGY': 'France',
         'FRA': 'Germany',
          'GBR': 'India',
          'IND': 'Japan',
         'JPN': 'Nigeria',
         'NGA': 'South Africa',
         'USA': 'United Kingdom',
         'ZAF': 'United States'}
```

```
In [3]: # Grouping the countries in their respective continents in a dictionary
        country_groups = {'EGY':'Africa', 'NGA':'Africa', 'ZAF':'Africa', 'CHN':'Asia', 'IND':'Asia', 'JPN':'Asia',
                           'FRA': 'Europe', 'DEU': 'Europe', 'GBR': 'Europe', 'CAN': 'North America', 'USA': 'North America'}
        country groups
Out[3]: {'EGY': 'Africa',
         'NGA': 'Africa',
          'ZAF': 'Africa',
         'CHN': 'Asia',
         'IND': 'Asia',
         'JPN': 'Asia',
         'FRA': 'Europe',
          'DEU': 'Europe',
         'GBR': 'Europe',
         'CAN': 'North America',
         'USA': 'North America'}
        Indicators
In [4]: import numpy as np
        import pandas as pd
        import wbgapi as wb
        import matplotlib.pyplot as plt
        %matplotlib inline
In [5]: # Creating a list of Indicator IDs for my first DataFrame
        indicator ids 1 = ['SP.POP.TOTL', 'SL.TLF.TOTL.IN', 'NY.GDP.MKTP.CD', 'NY.GDP.MKTP.KD.ZG', 'GC.DOD.TOTL.GD.ZS',
                            'FI.RES.TOTL.CD', 'BX.GSR.GNFS.CD', 'BM.GSR.GNFS.CD']
```

# Indicator IDs (indicator ids 2) for my second DataFrame is done in a similar method

### **DataFrames**

```
In [6]: # Creating a Pandas DataFrame from World Bank data

my_dataframe_1 = wb.data.DataFrame(indicator_ids_1, country_codes, time=range(2011, 2016))

#replacing most recent 5 years mrv=5 with time for chosen years

df = my_dataframe_1.unstack().stack(level=0) # using unstack and stack method to get the dataframe to my desired shape

# unstack() takes the indicators from being subcategories in the rows under country names to subcategories of year column

# applying stack() again on level = 0 takes the year columns to a sublevel of rows

# How it Looks
df.head(10)
```

#### Out[6]:

	series	BM.GSR.GNFS.CD	BX.GSR.GNFS.CD	FI.RES.TOTL.CD	GC.DOD.TOTL.GD.ZS	NY.GDP.MKTP.CD	NY.GDP.MKTP.KD.ZG	SL.TLF.TOTL.I
economy								
CAN	YR2011	5.684596e+11	5.467770e+11	6.581899e+10	NaN	1.793327e+12	3.146881	19147395
	YR2012	5.894798e+11	5.549615e+11	6.854634e+10	NaN	1.828366e+12	1.762223	19322866
	YR2013	5.890646e+11	5.600825e+11	7.193709e+10	NaN	1.846597e+12	2.329123	19546552
	YR2014	5.896265e+11	5.733055e+11	7.469996e+10	NaN	1.805750e+12	2.870036	19629145
	YR2015	5.347210e+11	4.961373e+11	7.975352e+10	NaN	1.556509e+12	0.659177	19747709
CHN	YR2011	1.826949e+12	2.008852e+12	3.254674e+12	NaN	7.551500e+12	9.550832	778977720
	YR2012	1.943247e+12	2.175092e+12	3.387513e+12	NaN	8.532230e+12	7.863736	782865417
	YR2013	2.120215e+12	2.355595e+12	3.880368e+12	NaN	9.570406e+12	7.766150	786673270
	YR2014	2.241603e+12	2.462902e+12	3.900039e+12	NaN	1.047568e+13	7.425764	791323527
	YR2015	2.002282e+12	2.360152e+12	3.405253e+12	NaN	1.106155e+13	7.041329	795251107

```
In [7]: # Multiindexing the rows
        dataframe 1 = df.iloc[:, ::-1]
        index = pd.MultiIndex.from product([country codes, [2011, 2012, 2013, 2014, 2015]],
                                           names=['Country', 'Year'])
        dataframe 1.index = index
In [8]: # Multiindexing the columns
        dataframe 1.columns = pd.MultiIndex.from tuples([('Population', 'Total'), ('Population', 'Total labor force'),
                                                          ('GDP', 'Growth (annual %)'), ('GDP', 'Gross (USD)'),
                                                         ('Economic strength', 'Central government debt (% of GDP)'),
                                                          ('Economic strength', 'Total reserves (USD)'),
                                                          ('Commerce', 'Exports (USD)'), ('Commerce', 'Imports (USD)')])
In [9]: # Re-arranging the columns using a variable called 't'
        t = list(dataframe 1.columns)
                                          # creates a list of column names
        # I want to swap positions of column 3 and 4
        t[2], t[3] = t[3], t[2]
        dataframe 1 = dataframe 1[t]
        This can also be manually done as below.
        dataframe 1 = dataframe 1[[('Population', 'Total'), ('Population', 'Total labor force'),
                                   ('GDP', 'Gross (USD)'), ('GDP', 'Growth (annual %)'),
                                   ('Economic strength', 'Central government debt (% of GDP)'),
                                   ('Economic strength', 'Total reserves (USD)'),
                                   ('Commerce', 'Exports (USD)'), ('Commerce', 'Imports (USD)')]]
Out[9]: "\nThis can also be manually done as below.\n\ndataframe 1 = dataframe 1[[('Population', 'Total'), ('Population', 'Tota
```

('GDP', 'Gross (USD)'), ('GDP', 'Growth (annual %)'), \n

('Commerce', 'Exports (USD)'), ('Commerce', 'Imports (USD)')]]\n"

('Economic strength', 'Total

1 labor force'),\n

reserves (USD)'), \n

('Economic strength', 'Central government debt (% of GDP)'), \n

Out[10]:

		Population		GDP		Economic strength		Commerce	
		Total	Total labor force	Gross (USD)	Growth (annual %)	Central government debt (% of GDP)	Total reserves (USD)	Exports (USD)	Imports (USD)
Country	Year								
CAN	2011	3.433933e+07	19147395.0	1.793327e+12	3.146881	NaN	6.581899e+10	5.467770e+11	5.684596e+11
	2012	3.471422e+07	19322866.0	1.828366e+12	1.762223	NaN	6.854634e+10	5.549615e+11	5.894798e+11
	2013	3.508295e+07	19546552.0	1.846597e+12	2.329123	NaN	7.193709e+10	5.600825e+11	5.890646e+11
	2014	3.543744e+07	19629145.0	1.805750e+12	2.870036	NaN	7.469996e+10	5.733055e+11	5.896265e+11
	2015	3.570291e+07	19747709.0	1.556509e+12	0.659177	NaN	7.975352e+10	4.961373e+11	5.347210e+11
CHN	2011	1.345035e+09	778977720.0	7.551500e+12	9.550832	NaN	3.254674e+12	2.008852e+12	1.826949e+12
	2012	1.354190e+09	782865417.0	8.532230e+12	7.863736	NaN	3.387513e+12	2.175092e+12	1.943247e+12
	2013	1.363240e+09	786673270.0	9.570406e+12	7.766150	NaN	3.880368e+12	2.355595e+12	2.120215e+12
	2014	1.371860e+09	791323527.0	1.047568e+13	7.425764	NaN	3.900039e+12	2.462902e+12	2.241603e+12
	2015	1.379860e+09	795251107.0	1.106155e+13	7.041329	NaN	3.405253e+12	2.360152e+12	2.002282e+12

In [11]: # The dataframe has a column with NaN values (there are a few inputs in this column though, let's see if it'll be useful

- # Please note:
- # some of the columns will be excluded in this analysis, they're just presented for informational purposes # and possible exploratory data analysis
- # I'll keep this dataframe as is for now and drop the columns not necessary as we as the NaN column when needed.

#### Out[12]:

	361163	SF.FOF.TOTE	LG.UGL.LLLC.KII.FC	LG.LLC.KNVX.23	LG.LLC.NOCL.23	LG.LLC.LO33.23	LG.LLC.ITTKO.23	LG.LLC.I OSL.ZS	LG.L
Country	Year								
CAN	2011	3.433933e+07	15644.540278	3.298016	14.707805	8.800576	59.040234	22.543932	
	2012	3.471422e+07	15336.624857	3.507259	14.900157	8.438532	59.723302	21.424611	
	2013	3.508295e+07	15750.811633	4.409954	15.549008	8.466956	58.888079	20.769341	
	2014	3.543744e+07	15588.487146	5.570376	16.119075	8.711767	57.254617	20.763125	
	2015	3.570291e+07	NaN	6.267257	15.546561	NaN	56.744193	21.067180	
CHN	2011	1.345035e+09	3295.784868	2.137640	1.835336	5.740233	14.624130	81.174003	
	2012	1.354190e+09	3466.019539	2.657515	1.953846	5.810062	17.308734	77.859893	
	2013	1.363240e+09	3757.185088	3.564878	2.053005	5.777010	16.731349	77.424467	
	2014	1.371860e+09	3905.317598	4.056660	2.339286	5.471266	18.552494	74.822887	
	2015	1.379860e+09	NaN	4.857004	NaN	NaN	19.069813	72.962076	

series SPPOPTOTI FGUSEFIECKHPC FGELCRNWXZS FGELCNUCLZS FGELCLOSSZS FGELCHYROZS FGELCFOSLZS FGE

€ |

```
In [13]: # Multiindexing the columns again
         dataframe 2.columns = pd.MultiIndex.from tuples([('Population', 'Total'),
                                                           ('Electricity T&D', 'Electricity consumption (kWh/capita)'),
                                                           ('Electricity production source (% of total)', 'Solar & Wind'),
                                                           ('Electricity production source (% of total)', 'Nuclear'),
                                                           ('Electricity T&D', 'Trans & Dist loss (% of output)'),
                                                           ('Electricity production source (% of total)', 'Hydro'),
                                                           ('Electricity production source (% of total)', 'Fossil fuels'),
                                                           ('Population', 'Access to electricity (% of population)')])
         dataframe 2 = dataframe 2[[('Population', 'Total'),
                                    ('Population', 'Access to electricity (% of population)'),
                                     ('Electricity T&D', 'Electricity consumption (kWh/capita)'),
                                     ('Electricity T&D', 'Trans & Dist loss (% of output)'),
                                     ('Electricity production source (% of total)', 'Solar & Wind'),
                                     ('Electricity production source (% of total)', 'Nuclear'),
                                     ('Electricity production source (% of total)', 'Hydro'),
                                     ('Electricity production source (% of total)', 'Fossil fuels')]]
         dataframe 2.head(10)
```

#### Out[13]:

	Population		Electricity T&D		Electricity production source (% of total)			total)
	Total	Access to electricity (% of population)	Electricity consumption (kWh/capita)	Trans & Dist loss (% of output)	Solar & Wind	Nuclear	Hydro	Fossil fuels
Year								
2011	3.433933e+07	100.000000	15644.540278	8.800576	3.298016	14.707805	59.040234	22.543932
2012	3.471422e+07	100.000000	15336.624857	8.438532	3.507259	14.900157	59.723302	21.424611
2013	3.508295e+07	100.000000	15750.811633	8.466956	4.409954	15.549008	58.888079	20.769341
2014	3.543744e+07	100.000000	15588.487146	8.711767	5.570376	16.119075	57.254617	20.763125
2015	3.570291e+07	100.000000	NaN	NaN	6.267257	15.546561	56.744193	21.067180
2011	1.345035e+09	99.848724	3295.784868	5.740233	2.137640	1.835336	14.624130	81.174003
2012	1.354190e+09	99.961929	3466.019539	5.810062	2.657515	1.953846	17.308734	77.859893
2013	1.363240e+09	99.996445	3757.185088	5.777010	3.564878	2.053005	16.731349	77.424467
	2011 2012 2013 2014 2015 2011 2012	Total  Year  2011 3.433933e+07  2012 3.471422e+07  2013 3.508295e+07  2014 3.543744e+07  2015 3.570291e+07  2011 1.345035e+09  2012 1.354190e+09	Year         Access to electricity (% of population)           2011         3.433933e+07         100.000000           2012         3.471422e+07         100.000000           2013         3.508295e+07         100.000000           2014         3.543744e+07         100.000000           2015         3.570291e+07         100.000000           2011         1.345035e+09         99.848724           2012         1.354190e+09         99.961929	Year         Access to electricity (% of population)         Electricity consumption (kWh/capita)           2011         3.433933e+07         100.000000         15644.540278           2012         3.471422e+07         100.000000         15336.624857           2013         3.508295e+07         100.000000         15750.811633           2014         3.543744e+07         100.000000         15588.487146           2015         3.570291e+07         100.000000         NaN           2011         1.345035e+09         99.848724         3295.784868           2012         1.354190e+09         99.961929         3466.019539	Year         Access to electricity (% of population)         Electricity consumption (kWh/capita)         Trans & Dist loss (% of output)           2011         3.433933e+07         100.000000         15644.540278         8.800576           2012         3.471422e+07         100.000000         15336.624857         8.438532           2013         3.508295e+07         100.000000         15750.811633         8.466956           2014         3.543744e+07         100.000000         15588.487146         8.711767           2015         3.570291e+07         100.000000         NaN         NaN           2011         1.345035e+09         99.848724         3295.784868         5.740233           2012         1.354190e+09         99.961929         3466.019539         5.810062	Total         Access to electricity (% of population)         Electricity consumption (kWh/capita)         Trans & Dist loss (% of output)         Solar & Wind           Year           2011         3.433933e+07         100.000000         15644.540278         8.800576         3.298016           2012         3.471422e+07         100.000000         15336.624857         8.438532         3.507259           2013         3.508295e+07         100.000000         15750.811633         8.466956         4.409954           2014         3.543744e+07         100.000000         15588.487146         8.711767         5.570376           2015         3.570291e+07         100.000000         NaN         NaN         6.267257           2011         1.345035e+09         99.848724         3295.784868         5.740233         2.137640           2012         1.354190e+09         99.961929         3466.019539         5.810062         2.657515	Year         Access to electricity (% of population)         Electricity consumption (kWh/capita)         Trans & Dist loss (% of output)         Solar & Nuclear           Year         Year         Total         Access to electricity (% of population)         Electricity consumption (kWh/capita)         Trans & Dist loss (% of output)         Nuclear           Year         Year	Year         Access to electricity (% of population)         Electricity consumption (kWh/capita)         Trans & Dist loss (% of output)         Solar & wind         Nuclear         Hydro           Year         Year </th

		Population		Electricity T&D	Electricity production source (% of total)					
		Total	Access to electricity (% of population)	Electricity consumption (kWh/capita)	Trans & Dist loss (% of output)	Solar & Wind	Nuclear	Hydro	Fossil fuels	
Country	Year									
	2014	1.371860e+09	100.000000	3905.317598	5.471266	4.056660	2.339286	18.552494	74.822887	
	2015	1.379860e+09	100.000000	NaN	NaN	4.857004	NaN	19.069813	72.962076	_

# **Data Analysis**

Use Pandas groupby() and pivot\_table() methods to construct 8 different summary statistics. They must include the following Pandas techniques:

- groupby() combined with aggregate(), filter(), transform(), and apply() methods.
- groupby() using an external key, the dictionary country\_groups you have constructed above.
- at least one summary statistics must use the pivot\_table() method.
- at least two summary statistics must use data from both DataFrames.

The necessary Pandas techniques are explained in Notebooks 2.8 and 2.9.

**Important:** Make sure your summary statistics make sense and tell a story. This story must be summarized in the first part of this assignment, "The Story".

This part is worth 10 marks: 1 mark for Python code for each summary statistic and 2 marks for comments explaining the Python code and the summary statistics.

```
In [14]: # Application of groupby
         gdp_max = dataframe_1.groupby(level='Country')[[('GDP', 'Gross (USD)')]].mean()
         gdp_max.sort_values(by=[('GDP', 'Gross (USD)')], ascending=False)
Out[14]:
                  GDP
                  Gross (USD)
          Country
             USA 1.685798e+13
             CHN 9.438274e+12
             JPN 5.411953e+12
             DEU 3.651388e+12
             GBR 2.848216e+12
             FRA 2.731172e+12
              IND 1.930025e+12
             CAN 1.766110e+12
             NGA 4.805336e+11
             ZAF 4.042793e+11
```

**EGY** 2.877005e+11

USA, China and Japan had higher avearge GDP than the rest of the countries between 2011 and 2015

```
In [15]: # GDP growth of the countries using groupby.filter()
    # Filter by average GDP growth more than 5%
    #dataframe_1.groupby('Country').filter(lambda x: x[('GDP','Growth (annual %)')].mean() > 3)
    growth = dataframe_1.groupby('Country').filter(lambda x: x[('GDP','Growth (annual %)')].mean() > 5)
    growth.groupby('Country')[[('GDP','Growth (annual %)')]].mean().sort_values([('GDP','Growth (annual %)')], ascending=Fal:
Out[15]:
    GDP
    Growth (annual %)
```

Country

CHN 7.929562
IND 6.498058
NGA 5.034347

China's GDP was the fastest growing between 2011-2015

```
In [16]: # The percentage of the labor force in the countries apply() method
         df_3 = dataframe_1[[('Population', 'Total')]].droplevel(level=0, axis=1)
         df 3 = df 3.reset index()
         df 4 = dataframe 1[[('Population', 'Total labor force')]].droplevel(level=0, axis=1)
         df 4 = df 4.reset index()
         def ratio(x):
             x['Total labor force'] /= df 3['Total']/100
             return x
         labor force percentage = df 4.groupby('Country').apply(ratio)
         labor force percentage.columns = ['Country', 'Year', 'labor force percetage']
         labor force percentage.groupby('Country')['labor force percetage'].mean()
Out[16]: Country
         CAN
                55.567898
         CHN
                57.749414
         DEU
                52.180651
         EGY
                32.302633
         FRA
                45.881623
         GBR
                51.592087
         IND
                36.040963
                51.508466
         JPN
                31.700477
         NGA
         USA
                50.113420
                37.488959
         ZAF
         Name: labor force percetage, dtype: float64
```

China, Canada, Germany, United Kingdom, Japan and the US have more than 50 percent of their population into the workforce

## Out[17]:

Commerce

**Exports (USD)** 

	min	mean	max
Country			
CHN	2.008852e+12	2.272519e+12	2.462902e+12
USA	2.143556e+12	2.275359e+12	2.392613e+12
DEU	1.575247e+12	1.672834e+12	1.773618e+12
JPN	7.847108e+11	8.644595e+11	9.306604e+11
GBR	8.037030e+11	8.284525e+11	8.679430e+11
FRA	7.775447e+11	8.173200e+11	8.535030e+11
CAN	4.961373e+11	5.462527e+11	5.733055e+11
IND	4.286309e+11	4.545416e+11	4.855830e+11
ZAF	9.634652e+10	1.130611e+11	1.269350e+11
NGA	4.904777e+10	8.680304e+10	1.024375e+11
EGY	3.756940e+10	4.503704e+10	4.860130e+10

## Out[18]:

Commerce

Imports (USD)

	. , ,		
	min	mean	max
Country			
USA	2.698073e+12	2.775889e+12	2.876564e+12
CHN	1.826949e+12	2.026859e+12	2.241603e+12
DEU	1.320209e+12	1.446217e+12	1.515877e+12
JPN	8.079867e+11	9.480099e+11	1.014813e+12
GBR	8.475310e+11	8.679509e+11	9.221976e+11
FRA	7.873782e+11	8.515478e+11	8.897318e+11
CAN	5.347210e+11	5.742703e+11	5.896265e+11
IND	4.918801e+11	5.477624e+11	5.799086e+11
ZAF	1.008028e+11	1.172173e+11	1.235595e+11
NGA	7.194744e+10	8.134336e+10	9.079363e+10
EGY	6.138110e+10	6.748850e+10	7.399600e+10

```
In [19]: profit = export_by_countries[('Commerce', 'Exports (USD)', 'mean')] - import_by_countries[('Commerce', 'Imports (USD)',
         profit.sort_values(ascending=False)
Out[19]: Country
         CHN
                2.456596e+11
                2.266173e+11
         DEU
         NGA
                5.459673e+09
               -4.156178e+09
         ZAF
               -2.245146e+10
         EGY
         CAN
              -2.801757e+10
         FRA
              -3.422773e+10
              -3.949841e+10
         GBR
              -8.355042e+10
         JPN
         IND
              -9.322084e+10
         USA
              -5.005302e+11
         dtype: float64
```

China, USA and Germany are the top 3 exporters and importers of good and services among the countries.

China, Germany and Nigeria are making profits.

```
In [20]: # Total reserves by continents using dataframe_1
# To groupby() using the dictionary country_groups (an external key) I need to reset the index of the multi-indexed datagreeset_df1 = dataframe_1.reset_index()
#print(reset_df)
# Now setting the index to the newly created column 'Country' assigning the value to a new dataframe country_idx_df_1 = reset_df1.set_index(['Country'])
#reset_df_groupby = reset_df.groupby(country_groups)[[('Economic strength', 'Total reserves (USD)')]].sum()
#reset_df_groupby on the new dataframe q to use country_groups
reserves_by_continent = country_idx_df_1.groupby(country_groups)[[('Economic strength', 'Total reserves (USD)')]].sum()
reserves_by_continent
```

#### Out[20]:

#### **Economic strength**

### Total reserves (USD)

Africa	5.076284e+11
Asia	2.572806e+13
Europe	2.447299e+12
North America	2.738945e+12

```
In [21]: reserves_list = dataframe_1.groupby('Country')[[('Economic strength', 'Total reserves (USD)')]].max()
    reserves_list.sort_values(by=[('Economic strength', 'Total reserves (USD)')], ascending=False)
```

Out[21]:

**Economic strength** 

Total reserves (USD)

Country	
CHN	3.900039e+12
JPN	1.295839e+12
USA	5.742681e+11
IND	3.533191e+11
DEU	2.488565e+11
FRA	1.845218e+11
GBR	1.481093e+11
CAN	7.975352e+10
ZAF	5.068808e+10
NGA	4.383064e+10
EGY	1.863754e+10

The selected Asian countries have the highest reserves than the rest due to China and Japan having the most amount of reserves at the top 2 position on the table.

#### Out[22]:

#### Electricity production source (% of total)

	Solar & Wind
Africa	0.536075
Asia	4.535155
Europe	13.502376
North America	5.393571

Europe has larger proportion of its electricty production by Solar and Wind energies.

```
In [23]: # Which countries used more renewable sources to generate electricity than fossil fuels?
         renewable = dataframe 2[[('Electricity production source (% of total)', 'Solar & Wind'),
                                           ('Electricity production source (% of total)', 'Nuclear'),
                                          ('Electricity production source (% of total)', 'Hydro')]]
         renewable[('Electricity production source (% of total)', 'Fossil')] = dataframe 2[[('Electricity production source (% of
                                                                                             'Fossil fuels')]]
         #removing multi-index from the columns
         renewable = renewable.droplevel(level=0, axis=1)
         renewable = renewable.reset index()
         renewable['Sum of renewable (% of total electricity prod.)'] = renewable[['Solar & Wind', 'Nuclear', 'Hydro']].sum(axis=
         <ipython-input-23-07ac4d89d187>:8: SettingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row indexer,col indexer] = value instead
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user guide/indexing.html#returning-a
         -view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-co
```

renewable[('Electricity production source (% of total)', 'Fossil')] = dataframe 2[[('Electricity production source (%

(vg

of total)',

## Out[24]:

#### Sum of renewable (% of total electricity prod.)

Country	
FRA	92.360655
CAN	78.305179
DEU	40.370703
GBR	35.661474
USA	31.704813
CHN	22.348338
NGA	19.140297
IND	18.718404
JPN	15.535208
EGY	8.843665

France and Canada generate most of their electricity from renewable sources

#### Out[25]:

#### Fossil fuels

Country	
ZAF	93.674061
EGY	91.156335
NGA	80.859703
IND	80.685692
JPN	79.925226
CHN	76.848665
USA	67.929200
GBR	63.655315
DEU	58.223146
CAN	21.313638
FRA	7.177624

Most countries rely very heavily on fossil fuels for electricity production with the only exception of Canada and France as seen in the previous summary.

#### Out[26]:

Population	Electricity T&D
Total	Electricity consumption (kWh/capita)

Country		
CAN	3.570291e+07	15750.811633
USA	3.207390e+08	13245.881928
JPN	1.278330e+08	8099.598695
FRA	6.654827e+07	7367.843768
DEU	8.168661e+07	7281.272174
GBR	6.511622e+07	5471.933475
ZAF	5.538637e+07	4566.323754
CHN	1.379860e+09	3905.317598
EGY	9.244255e+07	1685.818794
IND	1.310152e+09	804.516349
NGA	1.811375e+08	156.797152

Per capita electricity usage is very high in Canada and the US. The table shows that population doesn't have any impact on the energy consumption.

## Out[27]:

		Total	Solar & Wind	Nuclear	Hydro
Country	Year				
CAN	2011	3.433933e+07	3.298016	14.707805	59.040234
	2012	3.471422e+07	3.507259	14.900157	59.723302
	2013	3.508295e+07	4.409954	15.549008	58.888079
	2014	3.543744e+07	5.570376	16.119075	57.254617
	2015	3.570291e+07	6.267257	15.546561	56.744193
CHN	2011	1.345035e+09	2.137640	1.835336	14.624130
	2012	1.354190e+09	2.657515	1.953846	17.308734
	2013	1.363240e+09	3.564878	2.053005	16.731349
	2014	1.371860e+09	4.056660	2.339286	18.552494

**Electricity production source (% of total)** 

**Population** 

In [28]: #Using transform() method
 #normalised the column by dvinding the max value for each category
 comparison\_2.groupby('Country').transform(lambda x: x/x.max())

## Out[28]:

		Population	Electricity production source (% of total)		
		Total	Solar & Wind	Nuclear	Hydro
Country	Year				
CAN	2011	0.961808	0.526230	0.912447	0.988563
	2012	0.972308	0.559616	0.924380	1.000000
	2013	0.982636	0.703650	0.964634	0.986015
	2014	0.992564	0.888806	1.000000	0.958665
	2015	1.000000	1.000000	0.964482	0.950118
CHN	2011	0.974762	0.440115	0.784571	0.766873
	2012	0.981397	0.547151	0.835232	0.907651
	2013	0.987955	0.733966	0.877620	0.877374
	2014	0.994202	0.835219	1.000000	0.972872

The normalised dataframe above shows that use of Solar and Wind energy had been gradually increasing in all countries except Egypt. No data on Nigeria is available for this category.

In [29]: comparison\_2.groupby('Country')[[('Electricity production source (% of total)', 'Solar & Wind')]].mean().round(3)

Out[29]:

Electricity production source (% of total)

Solar & Wind

Country	
CAN	4.611
CHN	3.455
DEU	21.335
EGY	0.960
FRA	4.767
GBR	14.405
IND	4.819
JPN	5.332
NGA	0.000
USA	6.177
ZAF	0.648

Germany is leading in harnessing solar and wind energy follwed by the Unied Kingdom.