Project_1 Code (cleaned up) (1)-2

February 8, 2023

[5]:
```
!pip install wbdata
import wbdata
import numpy as np
import cufflinks as cf
import pandas as pd
cf.go_offline()
```

```
Requirement already satisfied: wbdata in /opt/conda/lib/python3.9/site-packages
(0.3.0)
Requirement already satisfied: decorator>=4.0 in /opt/conda/lib/python3.9/site-
packages (from wbdata) (5.0.9)
Requirement already satisfied: appdirs<2.0,>=1.4 in
/opt/conda/lib/python3.9/site-packages (from wbdata) (1.4.4)
Requirement already satisfied: requests>=2.0 in /opt/conda/lib/python3.9/site-
packages (from wbdata) (2.26.0)
Requirement already satisfied: tabulate>=0.8.5 in /opt/conda/lib/python3.9/site-
packages (from wbdata) (0.9.0)
Requirement already satisfied: idna<4,>=2.5 in /opt/conda/lib/python3.9/site-
packages (from requests>=2.0->wbdata) (3.1)
Requirement already satisfied: charset-normalizer~=2.0.0 in
/opt/conda/lib/python3.9/site-packages (from requests>=2.0->wbdata) (2.0.0)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in
/opt/conda/lib/python3.9/site-packages (from requests>=2.0->wbdata) (1.26.7)
Requirement already satisfied: certifi>=2017.4.17 in
/opt/conda/lib/python3.9/site-packages (from requests>=2.0->wbdata) (2021.10.8)
/opt/conda/lib/python3.9/site-packages/geopandas/_compat.py:111: UserWarning:

The Shapely GEOS version (3.10.3-CAPI-1.16.1) is incompatible with the GEOS
version PyGEOS was compiled with (3.10.4-CAPI-1.16.2). Conversions between both
will be slow.
```

[4]:
```
!rm ~/.cache/wbdata/0.3.0
```

1 Population Statistics: outputs a number of (male/female/people) when parameters, sex, age range and country is inputted.

[6]:
```
def population (year, sex, age_range, place):
    age_indexes = []
    total_pop = 0

    for i in range (0, 80, 5):
        age_indexes.append(f'{i:02d}' + f'{i+4:02d}')
    age_indexes.append("80UP")

# set variable for appropriate sex
    male_variable = {"SP.POP."+ age_index+".MA":"Males "+ age_index for␣
 ↪age_index in age_indexes}
    female_variable = {"SP.POP."+age_index+".FE":"Females "+age_index for␣
 ↪age_index in age_indexes}

    if sex == 'Male':
        variable = male_variable
    else:
        variable = female_variable
        if sex == 'Total':
            variable = female_variable
            variable.update(male_variable)
# select dataframe with selected variable and narrow it down into the correct␣
 ↪country and year

    df = wbdata.get_dataframe(variable, country = place)
    df.index = df.index.astype(int)
    df.reset_index (inplace = True)
    df = df[df["date"] == year]
#for loop until the correct age_range:
    # to prevent size error in the case where the age_range is greater than␣
 ↪provided data
    loop_count = int(age_range[1]/5)
    if sex == 'Total':
        if age_range[1] > 85:
            loop_count = 34
        for i in range(1, loop_count + 1):
            total_pop += df.iloc[0][i]
    else:
        if age_range[1] > 85:
            loop_count = 17
        for i in range(1, loop_count+ 1):
            total_pop += df.iloc[0][i]
```

```
    return total_pop

population(year=2010,sex='Total',age_range=(0,100),place='WLD')
```

[6]: 6969631911.0

2 Population DataFrames: returns a pandas dataframe indexed by region/country and year with columns giving counts of people in different age-sex groups.

[7]:
```
def population_by_sex_age (sex):
    age_indexes= []
    for i in range (0, 80, 5):
        age_indexes.append(f'{i:02d}' + f'{i+4:02d}')
    age_indexes.append("80UP")

#set variable for appropriate sex
    male_variable = {"SP.POP."+ age_index+".MA":"Males "+ age_index for␣
 ↪age_index in age_indexes}
    female_variable = {"SP.POP."+age_index+".FE":"Females "+age_index for␣
 ↪age_index in age_indexes}

    if sex == 'Male':
        variable = male_variable
    else:
        variable = female_variable
        if sex == 'Total':
            variable = female_variable
            variable.update(male_variable)
#making country/region and year as index
    df = wbdata.get_dataframe(variable)
    return df

population_by_sex_age(sex = 'Total')
```

[7]:

		Females 0004	Females 0509	Females 1014	\
country	date				
Africa Eastern and Southern	2021	53234090.0	47750830.0	43088865.0	
	2020	52265991.0	46911818.0	42069398.0	
	2019	51296626.0	46072800.0	40999618.0	
	2018	50354295.0	45238285.0	39886015.0	
	2017	49459497.0	44365105.0	38773390.0	
…		…	…	…	
Zimbabwe	1964	415631.0	341230.0	291110.0	
	1963	403496.0	331381.0	276213.0	

```
                                1962      391764.0      322013.0      256781.0
                                1961      380468.0      313078.0      239351.0
                                1960      369647.0      304571.0      223221.0

                                      Females 1519  Females 2024  Females 2529  \
country                         date
Africa Eastern and Southern     2021    37392619.0    32150758.0    28023647.0
                                2020    36335804.0    31355868.0    27330572.0
                                2019    35311876.0    30578412.0    26700947.0
                                2018    34334491.0    29841888.0    26141601.0
                                2017    33410378.0    29177045.0    25594212.0
…                                             …             …             …
Zimbabwe                        1964      204435.0      172015.0      138356.0
                                1963      196707.0      165838.0      134779.0
                                1962      193933.0      159673.0      131872.0
                                1961      189423.0      154060.0      129320.0
                                1960      183903.0      149117.0      126929.0

                                      Females 3034  Females 3539  Females 4044  \
country                         date
Africa Eastern and Southern     2021    24474164.0    20373836.0    16114329.0
                                2020    23844536.0    19607075.0    15395913.0
                                2019    23161560.0    18847517.0    14730960.0
                                2018    22432247.0    18101141.0    14153659.0
                                2017    21674320.0    17350716.0    13678514.0
…                                             …             …             …
Zimbabwe                        1964      119011.0      103374.0       85596.0
                                1963      117351.0       99845.0       85673.0
                                1962      115790.0       96033.0       86317.0
                                1961      113886.0       92892.0       86400.0
                                1960      111416.0       90906.0       85262.0

                                      Females 4549  …  Males 3539  Males 4044  \
country                         date                …
Africa Eastern and Southern     2021    12840580.0  …  19836395.0  15770587.0
                                2020    12524773.0  …  19161081.0  15076634.0
                                2019    12243730.0  …  18485600.0  14415738.0
                                2018    11978368.0  …  17803395.0  13828439.0
                                2017    11705198.0  …  17103010.0  13331062.0
…                                             …  …           …           …
Zimbabwe                        1964       78906.0  …     96367.0     79754.0
                                1963       75795.0  …     93470.0     80309.0
                                1962       71982.0  …     90350.0     81382.0
                                1961       68364.0  …     87864.0     81913.0
                                1960       65495.0  …     86458.0     81256.0

                                      Males 4549  Males 5054  Males 5559  \
```

```
country                       date
Africa Eastern and Southern   2021  12307798.0   9963920.0   7562962.0
                              2020  11954285.0   9627875.0   7279339.0
                              2019  11620415.0   9271944.0   6991100.0
                              2018  11294381.0   8911271.0   6708990.0
                              2017  10961721.0   8561827.0   6445607.0
…                                        …           …           …
Zimbabwe                      1964     73593.0     54848.0     44523.0
                              1963     71013.0     53388.0     43842.0
                              1962     67716.0     52338.0     43203.0
                              1961     64543.0     51427.0     42555.0
                              1960     62021.0     50489.0     41873.0

                                    Males 6064  Males 6569  Males 7074  \
country                       date
Africa Eastern and Southern   2021   5530561.0   4019492.0   2724146.0
                              2020   5359947.0   3937852.0   2665421.0
                              2019   5191655.0   3835788.0   2579929.0
                              2018   5031828.0   3722030.0   2477747.0
                              2017   4892796.0   3609954.0   2373716.0
…                                        …           …           …
Zimbabwe                      1964     35794.0     26784.0     18491.0
                              1963     35085.0     26346.0     17942.0
                              1962     34337.0     25937.0     17347.0
                              1961     33630.0     25489.0     16770.0
                              1960     33005.0     24956.0     16244.0

                                    Males 7579  Males 80UP
country                       date
Africa Eastern and Southern   2021   1559724.0   1085329.0
                              2020   1511511.0   1077480.0
                              2019   1452252.0   1050938.0
                              2018   1392035.0   1014714.0
                              2017   1338098.0    980011.0
…                                        …           …
Zimbabwe                      1964     10362.0      6542.0
                              1963     10053.0      6238.0
                              1962      9770.0      5927.0
                              1961      9485.0      5618.0
                              1960      9178.0      5316.0

[16492 rows x 34 columns]
```

3 Population Pyramids: Function that takes input a DataFrame with columns providing counts of people by age-sex group and constructs a population pyramid graph for visualizing the data

[8]:
```
import pandas as pd
import plotly.graph_objs as go

#creating sample dataframes to run the function
age_ranges = []
for i in range (0, 80, 5):
    age_ranges.append(f'{i:02d}' + f'{i+4:02d}')
age_ranges.append("80UP")
male_variables = {"SP.POP."+age_range+".MA":"Males "+age_range for age_range in␣
 ↪age_ranges}
female_variables = {"SP.POP."+age_range+".FE":"Females "+age_range for␣
 ↪age_range in age_ranges}
variables = male_variables
variables.update(female_variables)
df = wbdata.get_dataframe(variables,country="KOR")

def population_pyramids (dataframe, year):

    # first sort by age_range for y axis
    age_ranges = []
    for i in range (0, 80, 5):
        age_ranges.append(f'{i:02d}' + f'{i+4:02d}')
    age_ranges.append("80UP")

    male_variables = {"SP.POP."+age_range+".MA":"Males "+age_range for␣
 ↪age_range in age_ranges}
    female_variables = {"SP.POP."+age_range+".FE":"Females "+age_range for␣
 ↪age_range in age_ranges}
    variables = male_variables
    variables.update(female_variables)

    df = wbdata.get_dataframe(variables,country="WLD")
    #defined gender bins to contain only the columns of respective gender
    men_bins = df.loc[str(year),:].filter(regex="Male").values
    women_bins = -df.loc[str(year),:].filter(regex="Female").values

    #make figure
    fig = go.Figure()

    #Add traces to the figure for men and women, respectively using the defined␣
 ↪gender bins
    fig.add_trace(go.Bar(
```

```
                x = men_bins,
                y=[int(s[:2])+1 for s in age_ranges],
                name = 'Male',
                orientation = 'h',
                marker = dict(color = 'blue'),
                hoverinfo = 'skip'))

    fig.add_trace(go.Bar(x = women_bins,
                         y=[int(s[:2])+1 for s in age_ranges],
                         orientation='h',
                         name='Women',
                         marker=dict(color='pink'),
                         hoverinfo='skip'
                        ))
    #cleaned up the figure to make it viewer-friendly
    fig.update_layout(
    template = 'plotly_white',
    title = 'Age Pyramid World ' + str(2021),
    title_font_size = 24,
    barmode = 'relative',
    bargap = 0.0,
    bargroupgap = 0
    )

    return fig.show()
population_pyramids (df, 2021)
```

4 Animated Popuolation Pyramid: takes as input as a dataframe with columns providing counts of people by age-sex groups, with rows corresponding to different years, and constructs an animated "population pyramid" graph for visualizing how the population changes over time.

[9]:
```
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.animation import FuncAnimation, PillowWriter
from IPython.display import HTML

## creating sample dataframes to run the function
age_ranges = []
for i in range (0, 80, 5):
    age_ranges.append(f'{i:02d}' + f'{i+4:02d}')
age_ranges.append("80UP")
```

```
male_variables = {"SP.POP."+age_range+".MA":"Males "+age_range for age_range in␣
 ↪age_ranges}
female_variables = {"SP.POP."+age_range+".FE":"Females "+age_range for␣
 ↪age_range in age_ranges}
variables = male_variables
variables.update(female_variables)

df = wbdata.get_dataframe(variables,country="FIN")
df.index = df.index.astype(int)
df.reset_index (inplace = True)

def animated_population_pyramid (df):
    fig, ax = plt.subplots(figsize = (15,8))
    def animate(year):
        ax.clear()
        filtered_men = df[df['date'] == year].filter(regex="Male").values[0]
        filtered_women = -df[df['date'] == year].filter(regex="Female").
 ↪values[0]
        age = [int(s[:2])+1 for s in age_ranges]
        male = plt.barh (y=age, width = filtered_men, color = '#00008B')
        female = plt.barh (y=age, width = filtered_women, color = '#FFD1D6')

        # pass in labels and set limits for scaled visualization
        ax.set_xlim(-500_000, 500_000)
        ax.bar_label(male, padding = 3, labels = [f'{round(values, -3):,}' for␣
 ↪values in filtered_men])
        ax.bar_label(female, padding = 3, labels = [f'{-1* round(values, -3):
 ↪,}' for values in filtered_women])
        #loop over the edge, move tick marks and clean up generally
        for edge in ['top', 'right', 'bottom', 'left']:
            ax.spines[edge].set_visible(False)
        ax.tick_params(left = False)
        ax.get_xaxis().set_visible(False)
        ax.set_ylabel("Age Range")
        ax.legend([male,female],['Males', 'Females'])
        ax.set_title(f'Population of Finland in {year}', size = 18)
        #animate using FuncAnimation imports by implemeting the animate function
    animation = FuncAnimation(fig, animate, frames = range(df['date'].
 ↪min(),df['date'].max()+1))
    #implemeted HTML due to jupyter notebook limitation of visualizing gif file
    return HTML(animation.to_html5_video())
animated_population_pyramid (df)
```

[9]: <IPython.core.display.HTML object>

4.1 Project Description: comparative analysis of GDP vs. Average Years of Total Schooling in Finalnd and Colombia

4.1.1 These graphs are interactive methods in order to compare GDP Per Capita or Total Years of Schooling between Columbia and Finland.

1. We created an interactive plot that takes in a list of countries and compares their GDP per capita from 1960 to 2020.

[10]:
```
#GDP per capital by country
GDP_indicators = {"NY.GDP.PCAP.CD": "GDP per capita"}
GDP_data = wbdata.get_dataframe(GDP_indicators,
                                country = ['FIN', 'COL']).sort_values('date',␣
 ↪ascending = True)
GDP_data = GDP_data.unstack('country')
GDP_data.head()
GDP_data.iplot(xTitle="Date",
               yTitle="GDP Per Capita",
               title="GDP Per Capita Per Country Over Time")
```

2. This code chunk similarly compares average years of total schooling between Columbia and Finland. One country only took data points every 5 years so we dropped all other information for a uniform x-axis.

[11]:
```
#Average years of schooling by country
pd.options.plotting.backend = 'plotly'
school_label = {"BAR.SCHL.1519" : "Average years of total schooling (Total)"}
```

```
school_enrollment = wbdata.get_dataframe(school_label, country = ['FIN', 'COL'])
school_enrollment = school_enrollment.unstack('country').dropna(how='all')
school_enrollment.iplot(xTitle="Date",
                        yTitle="Years of Schooling",
                        title="Total Years of Schooling Segmented by Gender")
```

3. Since we observed the overall trend of GDP and average years of school for both countries, we now want to see the the correlation between them in each of the country.

[12]:
```
#Finland and Colombia School_Enrollment
school_label = {"BAR.SCHL.1519" : "Average years of total schooling (Total)",
        "BAR.SCHL.1519.FE" : "Average years of total schooling (Female)"
        }

finland_school_enrollment = wbdata.get_dataframe(school_label, country = "FIN")
finland_school_enrollment.reset_index(inplace=True)
finland_school_enrollment = finland_school_enrollment.groupby("date").sum().
 ↪replace(0,np.nan).dropna(how="any")

colombia_school_enrollment = wbdata.get_dataframe(school_label, country = "COL")
colombia_school_enrollment.reset_index(inplace=True)
colombia_school_enrollment = colombia_school_enrollment.groupby("date").sum().
 ↪replace(0,np.nan).dropna(how="any")
```

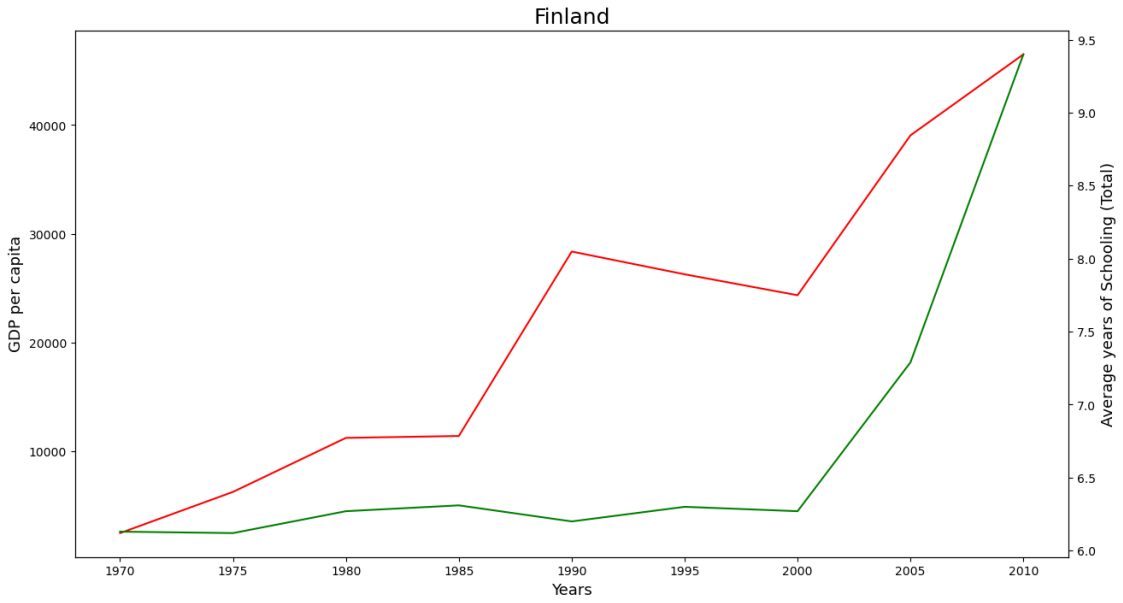
[13]:
```
#Finaland and Colombia GDP
GDP_indicators = {"NY.GDP.PCAP.CD": "GDP per capita"}

finland_GDP_data = wbdata.get_dataframe(GDP_indicators, country = "FIN")
finland_GDP_data.reset_index(inplace=True)

colombia_GDP_data = wbdata.get_dataframe(GDP_indicators, country = "COL")
colombia_GDP_data.reset_index(inplace=True)
```

[14]:
```
#combined dataframe of school enrollment and GDP for respective country
fin_education_GDP= finland_school_enrollment.join(finland_GDP_data.
 ↪set_index('date'), on='date')
col_education_GDP= colombia_school_enrollment.join(colombia_GDP_data.
 ↪set_index('date'), on='date')
```

[15]:
```
#Finland correlation between GDP and Average years of Schooling (Total)
import matplotlib.pyplot as plt
fig,finGDP = plt.subplots(figsize = (15,8))
finGDP.set_xlabel('Years', fontsize = 13)
finGDP.plot(fin_education_GDP["GDP per capita"], color = 'red')
finGDP.set_ylabel('GDP per capita', fontsize = 13)
finschool = finGDP.twinx()
```

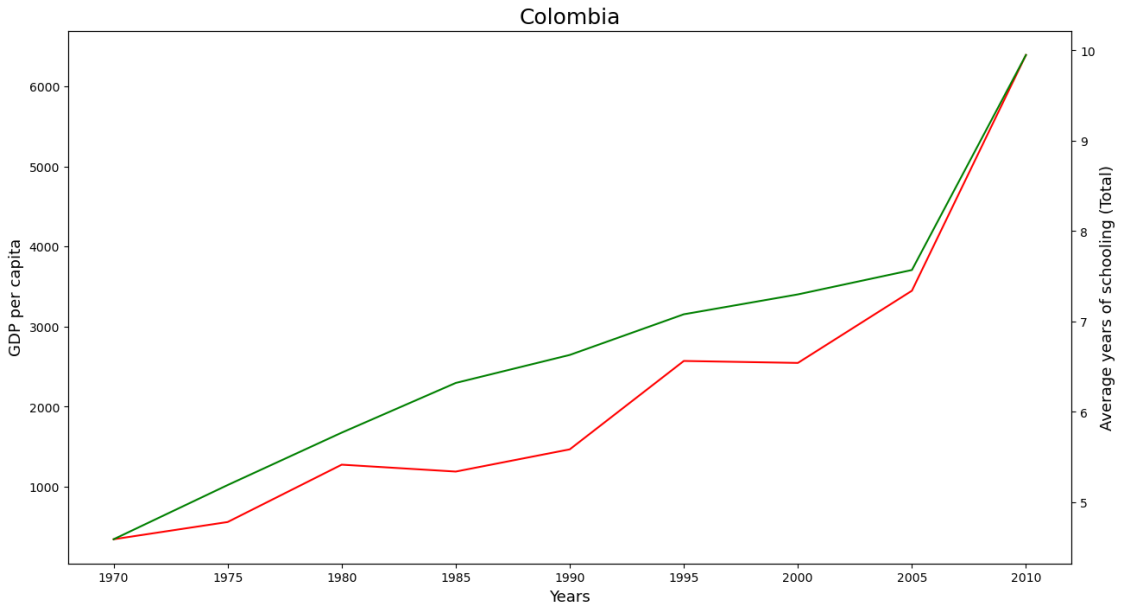
```
finschool.plot(fin_education_GDP["Average years of total schooling (Total)"],␣
 ↪color = 'green')
finschool.set_title("Finland", fontsize = 18)
finschool.set_ylabel('Average years of Schooling (Total)', fontsize = 13)
```

[15]: Text(0, 0.5, 'Average years of Schooling (Total)')



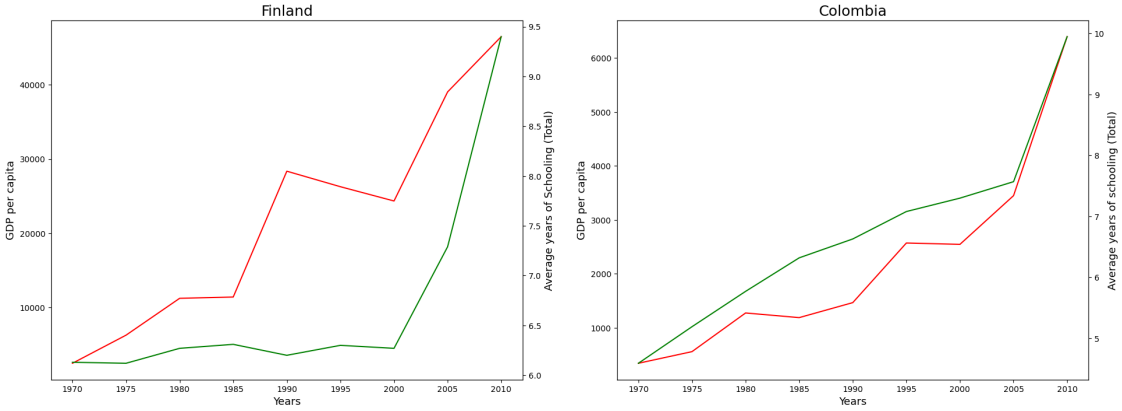
[16]:
```
#Colombia correlation between GDP and Average years of Schooling (Total)
import matplotlib.pyplot as plt
fig,colGDP = plt.subplots(figsize = (15,8))
colGDP.plot(col_education_GDP["GDP per capita"], color = 'red')
colGDP.set_ylabel('GDP per capita', fontsize = 13)
colGDP.set_xlabel('Years', fontsize = 13)
col_school = colGDP.twinx()
col_school.plot(col_education_GDP["Average years of total schooling (Total)"],␣
 ↪color = 'green')
col_school.set_title("Colombia", fontsize = 18)
col_school.set_ylabel("Average years of schooling (Total)", fontsize = 13)
```

[16]: Text(0, 0.5, 'Average years of schooling (Total)')



[17]:
```
#Comparative analysis between Finland and Colombia's correlation between GDP␣
 ↪and Average years of Schooling (Total)
import matplotlib.pyplot as plt
fig,(finGDP,colGDP) = plt.subplots(1,2, figsize = (23,8))
fig.suptitle('GDP and Average years of schooling in Finland and Colombia',␣
 ↪fontsize = 20)
finGDP.set_xlabel('Years', fontsize = 13)
finGDP.plot(fin_education_GDP["GDP per capita"], color = 'red')
finGDP.set_ylabel('GDP per capita', fontsize = 13)
finschool = finGDP.twinx()
finschool.plot(fin_education_GDP["Average years of total schooling (Total)"],␣
 ↪color = 'green')
finschool.set_title("Finland", fontsize = 18)
finschool.set_ylabel('Average years of Schooling (Total)', fontsize = 13)

colGDP.plot(col_education_GDP["GDP per capita"], color = 'red')
colGDP.set_ylabel('GDP per capita', fontsize = 13)
colGDP.set_xlabel('Years', fontsize = 13)
col_school = colGDP.twinx()
col_school.plot(col_education_GDP["Average years of total schooling (Total)"],␣
 ↪color = 'green')
col_school.set_title("Colombia", fontsize = 18)
col_school.set_ylabel("Average years of schooling (Total)", fontsize = 13)
```

[17]:
```
Text(0, 0.5, 'Average years of schooling (Total)')
```


GDP and Average years of schooling in Finland and Colombia
Finland
Colombia
GDP per capita
Average years of Schooling (Total)
Average years of schooling (Total)
Years
1970
1975
1980
1985
1990
1995
2000
2005
2010
10000
20000
30000
40000
1000
2000
3000
4000
5000
6000
6.0
6.5
7.0
7.5
8.0
8.5
9.0
9.5
5
6
7
8
9
10