UDACITY – DATA ANALYST NANODEGREE

PROJECT 1 – EXPLORE WEATHER TRENDS

I have started my analysis by exporting data using SQL Workspace

I have calculated moving average using window function, I decided to use 5-years-moving average, as 10-years might have been a bit too lagging especially considering how climate change has speed up in recent 50 years

```
SELECT *,
        avg(avg_temp) OVER(ORDER BY year
  ROWS BETWEEN 4 PRECEDING AND CURRENT ROW )
  as moving_average
from global_data;
```

```
SELECT *,
        avg(avg_temp) OVER (PARTITION BY city ORDER BY year
             ROWS BETWEEN 4 PRECEDING AND CURRENT ROW)
             as moving_avg
from city_data
WHERE city IN ('Warsaw','Wellington','London','Lima') AND country IN ('Peru','United Kingdom','Poland','New Zealand');
```

Then I have downloaded 2 CSV files, one with global data, second with cities where I thought about moving. Added COUNTRY in a WHERE condition as dataset also included city of London but in Canada which I'm not interested in

Then I've moved on to Jupyter Notebook

First step is to import all libraries and two .csv files

```
In [1]: import pandas as pd
        import seaborn as sns
        from sklearn.linear_model import LinearRegression
        import numpy as np

        #importing csv files
        global_temperature = pd.read_csv(r'''C:\Users\pauli\Untitled Folder 1\Project 1\global_temperature.csv''')
        city_temperature = pd.read_csv(r'''C:\Users\pauli\Untitled Folder 1\Project 1\cities_temperature.csv''')

        #checking they're imported correctly
        print(global_temperature.head(5))
        print(city_temperature.head(5))

   year  avg_temp  moving_average
0  1750      8.72        8.720000
1  1751      7.98        8.350000
2  1752      5.78        7.493333
3  1753      8.39        7.717500
4  1754      8.47        7.868000
   year  city country  avg_temp  moving_avg
0  1881  Lima    Peru     15.75   15.750000
1  1882  Lima    Peru     15.88   15.815000
2  1883  Lima    Peru     16.18   15.936667
3  1884  Lima    Peru     16.14   15.987500
4  1885  Lima    Peru       NaN   15.987500
```

Next step is to add columns to global_temperature dataset and rename moving_avg column so it fits the other dataframe

```
In [2]: #adding columns to global_temp dataset so they are the same as cities in order to union them later
        global_temperature['country'] = 'global'
        global_temperature['city'] = 'global'

        #renaming moving_average column name so it fits cities_temp name
        global_temperature = global_temperature.rename(columns={'moving_average':'moving_avg'})
        print(global_temperature.head(5))

   year  avg_temp  moving_avg country    city
0  1750      8.72    8.720000  global  global
1  1751      7.98    8.350000  global  global
2  1752      5.78    7.493333  global  global
3  1753      8.39    7.717500  global  global
4  1754      8.47    7.868000  global  global
```

Then unioning them and getting rid of years before 1750, as there were mostly missing values

```
In [3]: #union of datasets
        temp = pd.concat([city_temperature,global_temperature])
        temp = temp[temp['year']>=1750]
        print(temp)
```

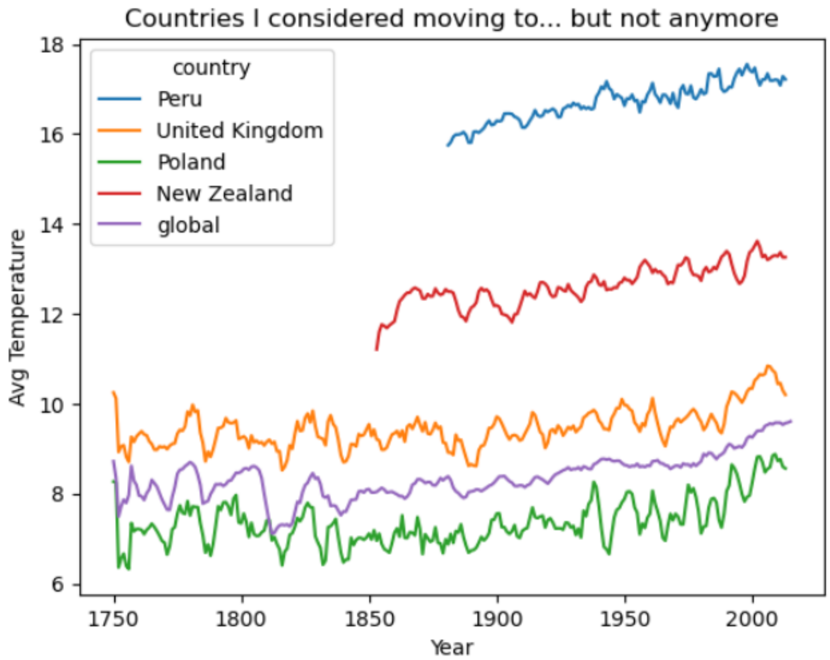
```
     year    city country  avg_temp  moving_avg
0    1881    Lima    Peru     15.75   15.750000
1    1882    Lima    Peru     15.88   15.815000
2    1883    Lima    Peru     16.18   15.936667
3    1884    Lima    Peru     16.14   15.987500
4    1885    Lima    Peru       NaN   15.987500
..    ...     ...     ...       ...         ...
261  2011  global  global      9.52    9.578000
262  2012  global  global      9.51    9.534000
263  2013  global  global      9.61    9.570000
264  2014  global  global      9.57    9.582000
265  2015  global  global      9.83    9.608000

[1088 rows x 5 columns]
```

Then I was trying to be clever and added a bit of humour (which probably was funny only to myself, but I got to get through this heatwave we're having in Poland right now) **–** looking at this graph, it's clearly visible that Poland was the coolest country and its average values are still below global average

What's also interesting, is that we have started measuring temperatures in countries outside Europe only in second half of 19th century and as NASA claims, we can only really start trusting these measurements, especially on global basis, from 1880 onward

https://climate.nasa.gov/faq/21/why-does-the-temperature-record-shown-on-your-vital-signs-page-begin-at-1880/

```
In [4]: #plotting the graph for countries I've chosen
        ax = sns.lineplot(x='year',y='moving_avg', hue='country', data=temp)
        ax.set(xlabel='Year',
               ylabel='Avg Temperature',
               #trying to be funny
               title='Countries I considered moving to... but not anymore')

Out[4]: [Text(0.5, 0, 'Year'),
         Text(0, 0.5, 'Avg Temperature'),
         Text(0.5, 1.0, 'Countries I considered moving to... but not anymore')]
```

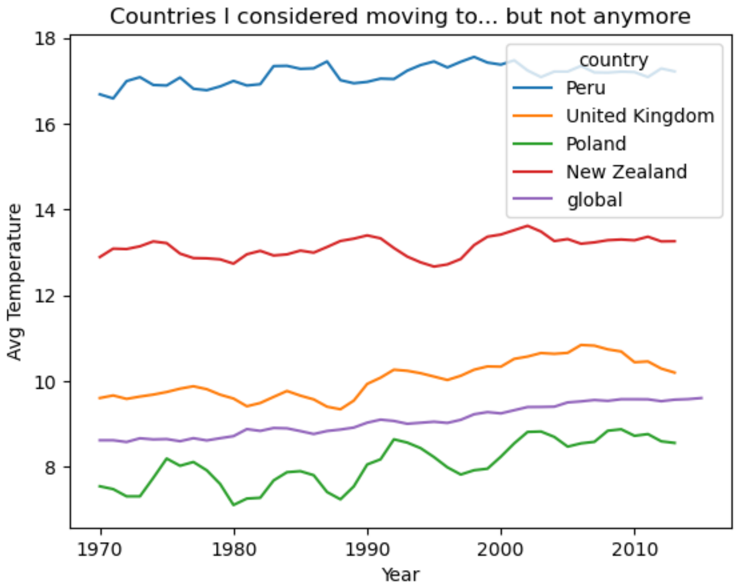


It is visible that temperatures are rising on both global scale and for chosen countries, but I decided to use Linear Regression to establish which country is getting hotter the quickest – looks like it's Peru, and it hasn't been getting that hot in Poland

```
In [5]: #it's clearly visible from the graph that trend is positive for all countries,
        #but using Linear Regression to check its value for all of them


        reg = LinearRegression()

        cities = temp['city'].unique()
        for city in cities:
            #filtering dataframe for one city only, so that linear regression is fit to each city separately
            city_data = temp[temp['city'] == city]
            reg.fit(city_data[['year']], city_data['moving_avg'])
            city_trend = reg.coef_[0]
            print(f"{city} Temperature Trend: {city_trend:.4f} degrees per year")

        Lima Temperature Trend: 0.0103 degrees per year
        London Temperature Trend: 0.0033 degrees per year
        Warsaw Temperature Trend: 0.0035 degrees per year
        Wellington Temperature Trend: 0.0081 degrees per year
        global Temperature Trend: 0.0045 degrees per year
```

Nevertheless, being aware that the process has speed up in last 50 years and I would not like to make any hasty decisions nor judgment, I have decided to redo the process, but only on data from 1970, and from this perspective, looks like capitalism has made its mark on Poland in the last 60 years and resulted in quite an increase in average temperature

```
In [6]: #plotting the graph for countries I've chosen
        after_1970 = temp[temp['year']>=1970]
        ax = sns.lineplot(x='year',y='moving_avg', hue='country', data=after_1970)
        ax.set(xlabel='Year',
               ylabel='Avg Temperature',
               #trying to be funny
               title='Countries I considered moving to... but not anymore')

Out[6]: [Text(0.5, 0, 'Year'),
         Text(0, 0.5, 'Avg Temperature'),
         Text(0.5, 1.0, 'Countries I considered moving to... but not anymore')]
```




```
In [7]: cities = after_1970['city'].unique()
        for city in cities:
            city_data = after_1970[after_1970['city'] == city]
            reg.fit(city_data[['year']], city_data['moving_avg'])
            city_trend = reg.coef_[0]
            print(f"{city} Temperature Trend: {city_trend:.4f} degrees per year")

        Lima Temperature Trend: 0.0107 degrees per year
        London Temperature Trend: 0.0286 degrees per year
        Warsaw Temperature Trend: 0.0322 degrees per year
        Wellington Temperature Trend: 0.0089 degrees per year
        global Temperature Trend: 0.0256 degrees per year
```

The last step was to calculate correlation coefficient between Poland and global trend, and there is indeed a very strong positive correlation

In [8]:
```
global_and_poland = temp[temp['country'].isin(['global','Poland'])]
print(global_and_poland.head(5))
```

```
     year    city country  avg_temp  moving_avg
411  1750  Warsaw  Poland      8.27      8.2700
412  1751  Warsaw  Poland      8.23      8.2500
413  1752  Warsaw  Poland      2.58      6.3600
414  1753  Warsaw  Poland      7.17      6.5625
415  1754  Warsaw  Poland      7.08      6.6660
```

In [9]:
```
global_and_poland=global_and_poland[['year','country','moving_avg']]
#removing years with NaN values
global_and_poland = global_and_poland[global_and_poland['year']<=2013]
```

In [10]:
```
global_and_poland = global_and_poland.pivot(index='year', columns='country', values='moving_avg')
print(global_and_poland)
```

```
country  Poland    global
year
1750     8.2700  8.720000
1751     8.2500  8.350000
1752     6.3600  7.493333
1753     6.5625  7.717500
1754     6.6660  7.868000
...         ...       ...
2009     8.8800  9.580000
2010     8.7280  9.580000
2011     8.7680  9.578000
2012     8.6000  9.534000
2013     8.5620  9.570000

[264 rows x 2 columns]
```

In [11]:
```
np.corrcoef(global_and_poland['Poland'], global_and_poland['global'])
```

Out[11]:
```
array([[1.        , 0.75252915],
       [0.75252915, 1.        ]])
```