Exploring Weather Trends

March 29, 2019

1 Reading source data

First we need to import the necessary python libraries. For importing the CSV files I chose pandas. For plotting the requested plots in the project I chose multiple plotting libraries. This for the reason that I already get to know them better. In general I chose the libraries pandas, numpy, seaborn, pyplot (matplotlib), patches (matplotlib) and plotting (pandas).

```
In [2]: import pandas as pd
        import numpy as np
        import seaborn as sns
        import matplotlib.pyplot as plt
        from pandas.plotting import table
        import matplotlib.patches as mpatches
```

For exporting the data I used the following SQL queries:
SELECT * FROM city_data WHERE city = 'Bern'
SELECT * FROM city_list
SELECT * FROM global_data

After importing the libraries we want to import the CSV source data files. Note: the backslashes need to be escaped.

```
In [3]: city_data = pd.read_csv("C:\\Users\\patri\\Desktop\\Udacity\\Project1\\city_data.csv")
        city_list = pd.read_csv("C:\\Users\\patri\\Desktop\\Udacity\\Project1\\city_list.csv")
        global_data = pd.read_csv("C:\\Users\\patri\\Desktop\\Udacity\\Project1\\global_data.c
```

Let's take a quick look at the data files that we know what we are talking about. First I will analyze the city_data.csv file and visualize the first five rows.

```
In [4]: city_data.head(5)
```

```
Out[4]:    year  city      country  avg_temp
        0  1743  Bern  Switzerland      3.54
        1  1744  Bern  Switzerland      8.19
        2  1745  Bern  Switzerland      0.36
        3  1746  Bern  Switzerland       NaN
        4  1747  Bern  Switzerland       NaN
```

So the file is containing historic temperature average information for the closest city. To further analyze the data I create pandas data frames.

```
In [5]: df_city_data = pd.DataFrame(data=city_data)
        df_global_data = pd.DataFrame(data=global_data)
```

The function describe() gives me an overview over the numeric fields contained in the data frames. I will execute this function for both data sets relevant for the first question of the project (city_data, global_data).

```
In [6]: df_city_data.describe()
```

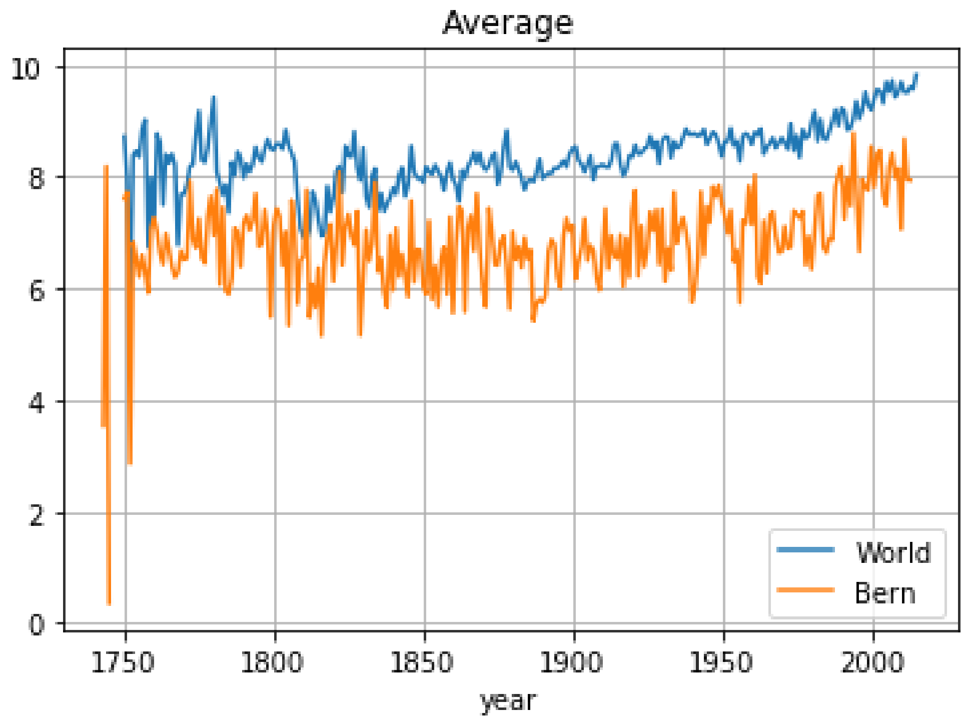
```
Out[6]:               year    avg_temp
        count   271.000000  267.000000
        mean   1878.000000    6.808577
        std      78.375166    0.861983
        min    1743.000000    0.360000
        25%    1810.500000    6.390000
        50%    1878.000000    6.830000
        75%    1945.500000    7.315000
        max    2013.000000    8.780000
```

```
In [7]: df_global_data.describe()
```

```
Out[7]:               year    avg_temp
        count   266.000000  266.000000
        mean   1882.500000    8.369474
        std      76.931788    0.584747
        min    1750.000000    5.780000
        25%    1816.250000    8.082500
        50%    1882.500000    8.375000
        75%    1948.750000    8.707500
        max    2015.000000    9.830000
```

These descriptions tell me already that the global average temperature was significantly higher than the average temperature in Bern (8.37 compared to 6.81). I can use this information to validate the line plot that I have to create later on.

```
In [8]: ax = df_global_data.plot(grid=0.5,title='Average',
                                 x='year',y='avg_temp')
        df_city_data.plot(grid=0.5,title='Average',x='year',
                          y='avg_temp',ax=ax).legend(["World", "Bern"]);
```



Visualizing just the average temperatures in a line chart shows that the data set for bern contains data even from way before 1750.

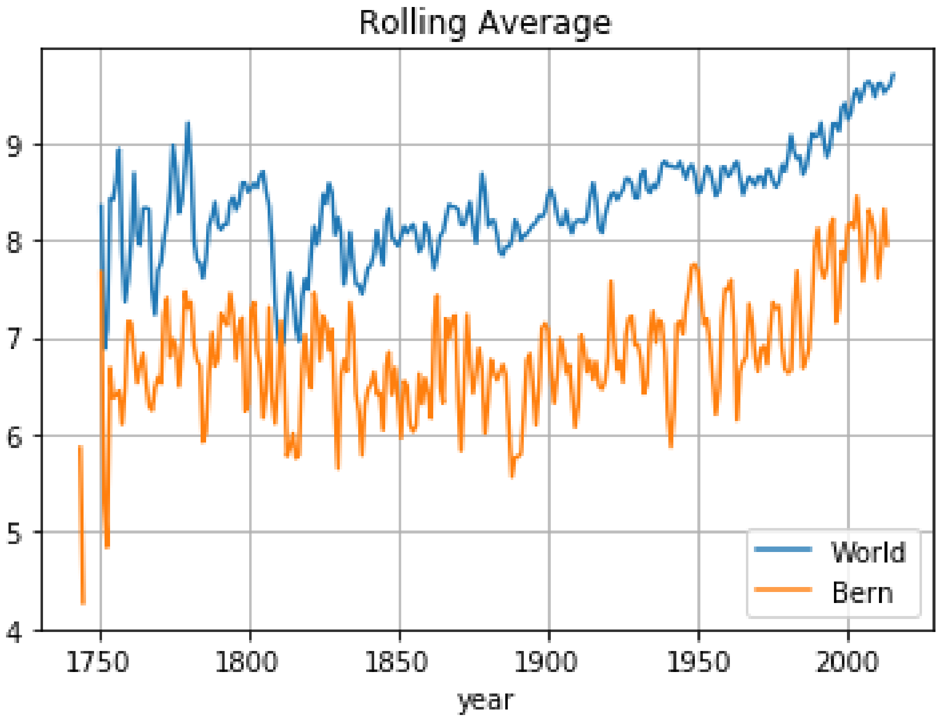
2 Moving average

For the lineplot I need to add an additional column to both of the data frame. In this column I will store the calculated rolling mean for each row. The "2" in the rolling function set the size of the moving window. This is the number of observations used for calculating the statistic. Each window will be a fixed size.

```
In [9]: df_global_data['rolling_mean_2'] = global_data['avg_temp'].rolling(2).mean()
        df_city_data['rolling_mean_2'] = city_data['avg_temp'].rolling(2).mean()
```

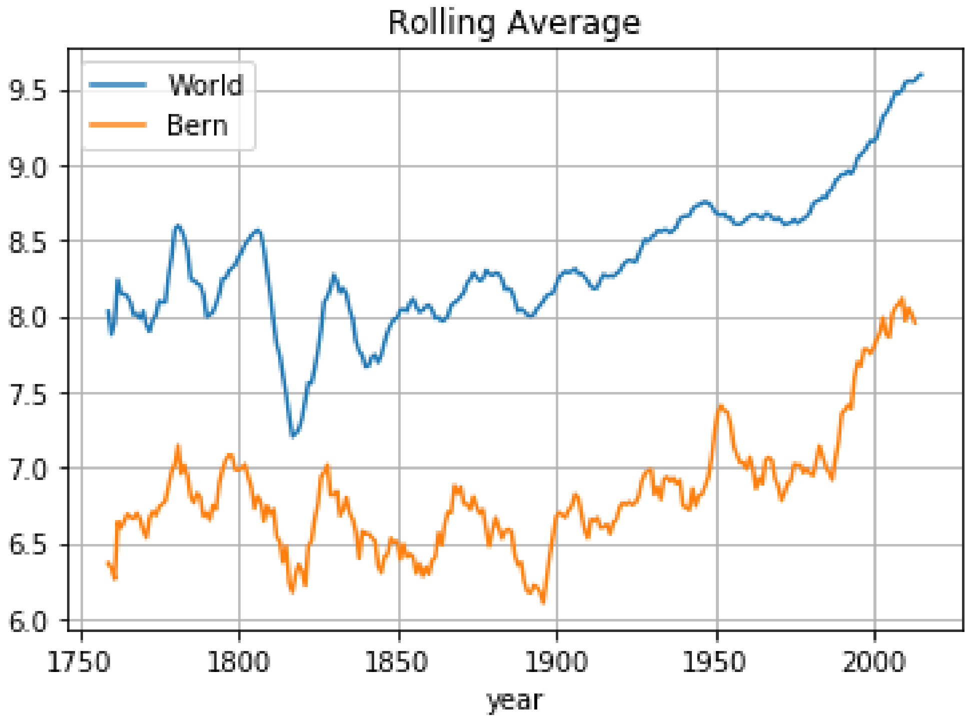
Now I am ready to set up the lineplot with the newly created column as the y-axis values and the year column as the x-axis values. For better visualization I additionally enable a grid and rename the labels for each data frame to ("World" and "Bern"). Finally I am setting a title for the line plot ("Rolling Average Temperature Bern vs. World").

```
In [10]: ax = df_global_data.plot(grid=0.5,title='Rolling Average',
                                  x='year',y='rolling_mean_2')
         df_city_data.plot(grid=0.5,title='Rolling Average',x='year',
                           y='rolling_mean_2',ax=ax).legend(["World", "Bern"]);
```



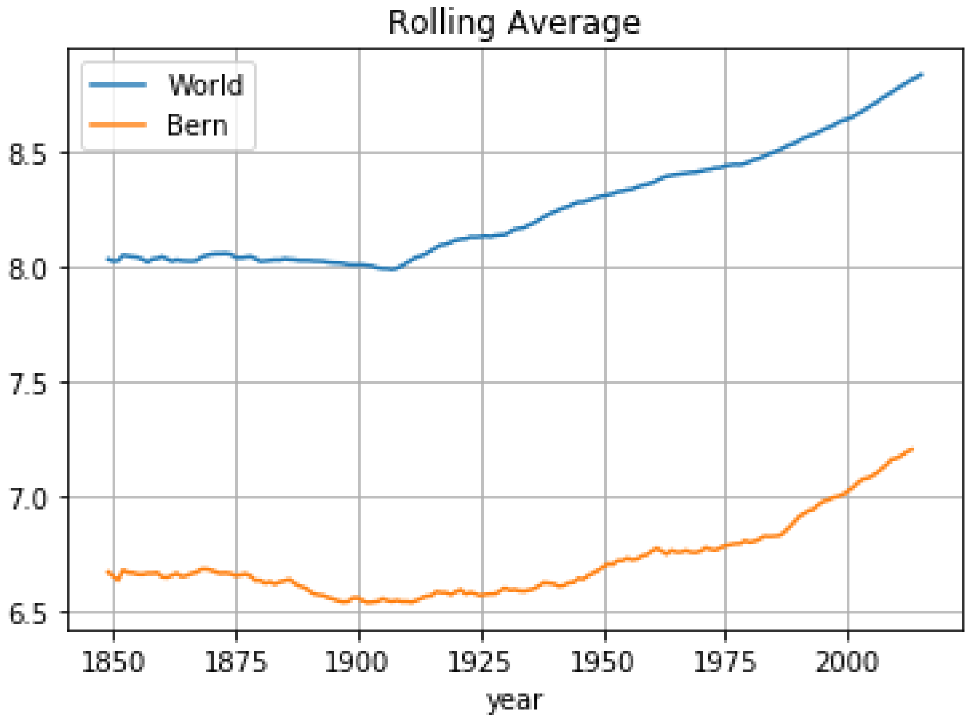
1. Observation: The plot seems to be correct compared to the output of the describe() function in the early stages of this project. It seems that the temperatures of Bern suffer more and higher up and downs than the global temperature. We can now play with the window size (e.g. 10 or 100) to see if there are any differences.

```
In [11]: df_global_data['rolling_mean_10'] = global_data['avg_temp'].rolling(10).mean()
         df_city_data['rolling_mean_10'] = city_data['avg_temp'].rolling(10).mean()
         ax = df_global_data.plot(grid=0.5,title='Rolling Average',x='year',
                                  y='rolling_mean_10')
         df_city_data.plot(grid=0.5,title='Rolling Average',x='year',
                           y='rolling_mean_10',ax=ax).legend(["World", "Bern"]);
```



2. Observation: The graph with window 10 shows that in the last 50 years it was a very consistent increase of the average temperature for both world and bern. Before that timeframe the temperature was very consistent for both datasets with just many up and downs.

```
In [12]: df_global_data['rolling_mean_100'] = global_data['avg_temp'].rolling(100).mean()
         df_city_data['rolling_mean_100'] = city_data['avg_temp'].rolling(100).mean()
         ax = df_global_data.plot(grid=0.5,title='Rolling Average',
                                  x='year',y='rolling_mean_100')
         df_city_data.plot(grid=0.5,title='Rolling Average',x='year',
                           y='rolling_mean_100',ax=ax).legend(["World", "Bern"]);
```

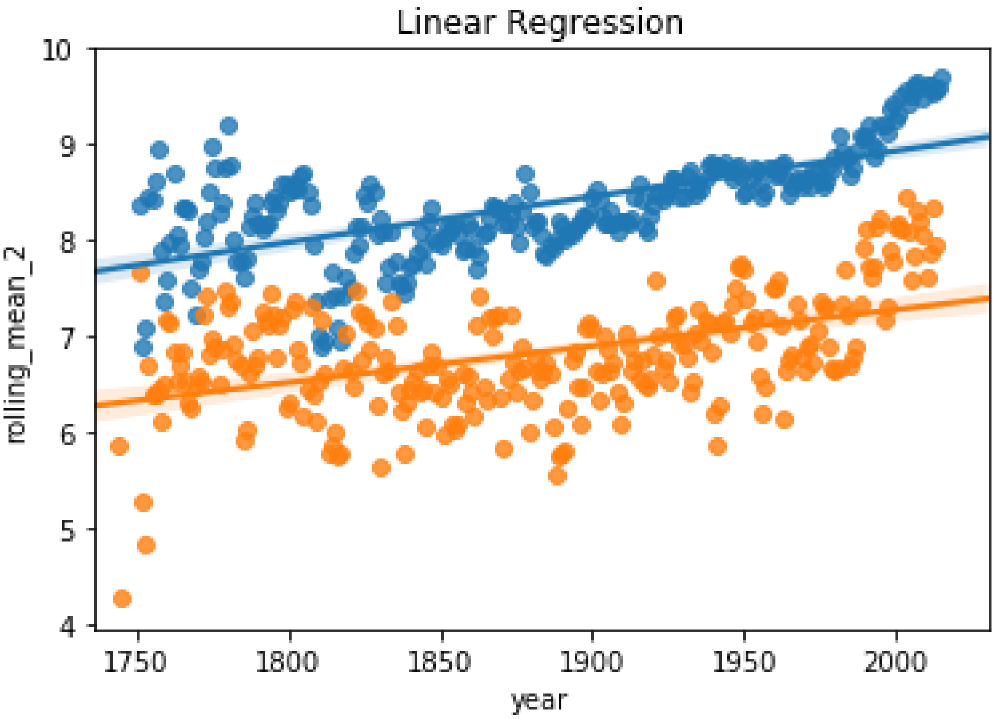


3. Observation: The moving average line chart with windows size 100 shows that the temperature for both datasets was even falling between 1875 and 1900. Somehow the trend then skips to ascending for any of the following years.

3 Linear Regression

```
In [13]: sns.regplot(x='year',y='rolling_mean_2',data=df_global_data)
         sns.regplot(x='year',y='rolling_mean_2',
                     data=df_city_data).set_title('Linear Regression')
```

```
Out[13]: Text(0.5,1,'Linear Regression')
```

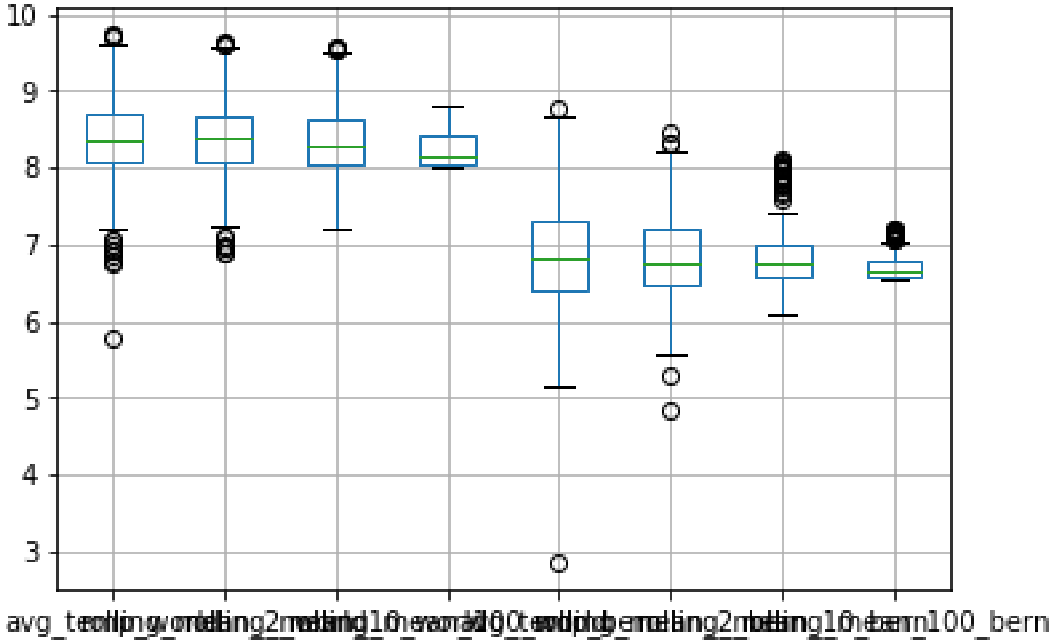


4. Observation: The linear regression for the complete dataset shows that the global rolling average temperature has a higher slope than the rolling average temperature of Bern, Switzerland. This means that in general the global temperature increases fast then the local temperature in Bern.

4 Boxplot

```
In [14]: merged_inner = pd.merge(left=df_global_data,right=df_city_data,
                                  left_on='year', right_on='year')
         merged_inner.shape
         merged_inner
         merged_inner = merged_inner.drop(['city', 'country'], axis=1)
         merged_inner.columns = ['year','avg_temp_world','rolling_mean_2_world',
                                  'rolling_mean_10_world','rolling_mean_100_world',
                                  'avg_temp_bern','rolling_mean_2_bern',
                                  'rolling_mean_10_bern','rolling_mean_100_bern']
         merged_inner.boxplot(column=['avg_temp_world','rolling_mean_2_world',
                                      'rolling_mean_10_world','rolling_mean_100_world',
                                      'avg_temp_bern','rolling_mean_2_bern',
                                      'rolling_mean_10_bern','rolling_mean_100_bern'])
```

```
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x20f63934b38>
```



5. Observation: Boxplotting the average temperature shows the significantly higher average and rolling average temperatures for the world compared to Bern.