Data Analyst Nanodegree

Project 1 – Explore weather data trend

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https://github.com/rogeriocarneiro/Udacity_NanoDegree_DataAnalyst

Summary

Step 1 – Extracting the data from the database.

It's shown below the SQL codes run to extract the data from the database provided and the 10 first rows from the query results.

EXTRACTING CITY TEMPERATURE

```
select
        cd.year
        , cl.city
        , cl.country
        , cd.avg_temp
from city_list cl
left join city_data cd on cd.city = cl.city
        where cl.country = 'Brazil'
        and cl.city ilike 'Rio De Janeiro'
```

	year	city	country	avg_temp
0	1832	Rio De Janeiro	Brazil	23.05
1	1833	Rio De Janeiro	Brazil	24.11
2	1834	Rio De Janeiro	Brazil	23.27
3	1835	Rio De Janeiro	Brazil	22.73
4	1836	Rio De Janeiro	Brazil	22.91
5	1837	Rio De Janeiro	Brazil	22.29
6	1838	Rio De Janeiro	Brazil	22.81
7	1839	Rio De Janeiro	Brazil	22.54
8	1840	Rio De Janeiro	Brazil	23.32
9	1841	Rio De Janeiro	Brazil	22.97

EXTRACTING GLOBAL TEMPERATURE

```
select * from global_data
```

	year	avg_temp
0	1750	8.72
1	1751	7.98
2	1752	5.78
3	1753	8.39
4	1754	8.47
5	1755	8.36
6	1756	8.85
7	1757	9.02
8	1758	6.74
9	1759	7.99

Step 2 – Scanning the data

This way we can have a first picture of what's inside the datasets, as the count of rows with no non-null values for each series.

Firstly, the shape information of each dataset was retrieved. Then both data frames were merged using the **'year'** column in order to have them sharing the same time span, with or without non-null values.

With the data frame normalized using the year column, it's verified the first year where both temperatures were measured. This way the analysis can be carried out from that year forward, in order to minimize the chance of using a not balanced data frame. This year is 1832 as seen in the third row at the table below.

	CITY TEMPERATURE	GLOBAL TEMPERATURE
df.shape()	Columns: 4 Rows: 182	Columns: 2 Rows: 262

df.info()	`Data columns (total 5 columns):`
	` #  Column  Non-Null Count  Dtype`
	`---  ------  --------------  -----`
	` 0  year  266 non-null  int64`
	` 1  global_temp  266 non-null  float64`
	` 2  city  182 non-null  object`
	` 3  country  182 non-null  object`
	` 4  city_temp  175 non-null  float64`
	`dtypes: float64(2), int64(1), object(2)`	

`df.loc[df[_].first_valid_index()].iloc[0]`	1832	1750

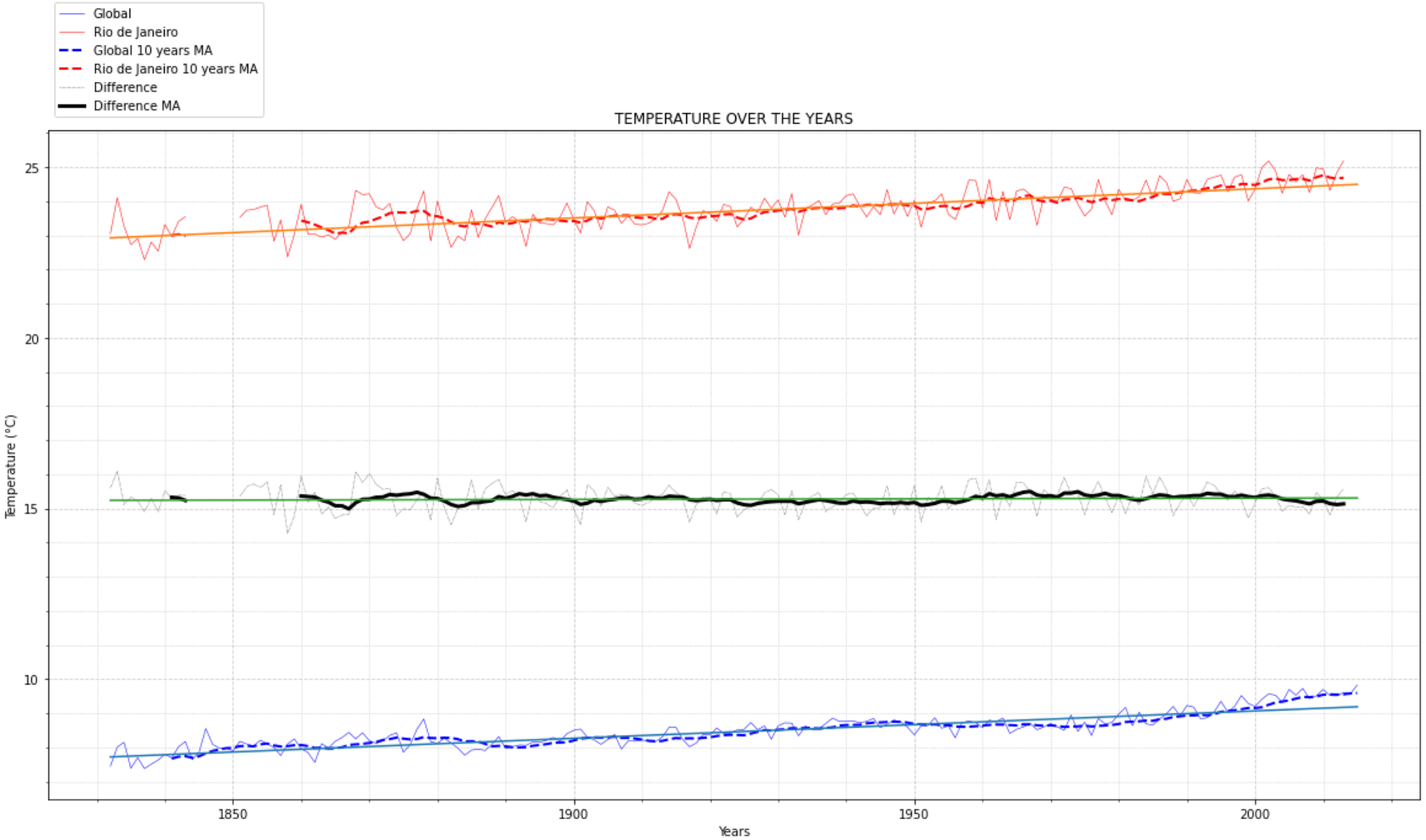
Step 3 – Calculating the moving averages and data visualization

The moving average chosen to perform this analysis considers a window of 10 years. The moving averages of the city_temp and global_temp and the difference between them were calculated and appended to the data frame simply using the rolling() and mean() methods as show below:

```
df['global_10y_MA']   = df['global_temp'].rolling(10).mean()
df['city_10y_MA']     = df['city_temp'].rolling(10).mean()

df['diff']            = df['city_temp'] - df['global_temp']
df['diff_MA']         = df['diff'].rolling(10).mean()
```

Once these calculations were made, it was possible to generate a reasonable visualization on what the datasets contains.

The chart is presented in the next page, as follows.


Global
Rio de Janeiro
Global 10 years MA
Rio de Janeiro 10 years MA
Difference
Difference MA
TEMPERATURE OVER THE YEARS
Temperature (°C)
25
20
15
10
1850
1900
1950
2000
Years

Step 4 – Data analysis

The boundary values for the moving averages series are:

	CITY TEMPERATURE	GLOBAL TEMPERATURE	DIFFERENCE
MIN (YEAR)	22.98 (1843)	7.67 (1841)	14.99 (1867)
MAX (YEAR)	24.76 (2010)	9.59 (2015)	15.5 (1967)
VARIATION	1.784	1.923	0.510

Other overall value that could explain more the behavior of the temperatures is the trend of the temperature change over the years and how many years it would take to the temperature rise in 1 ºC. The calculated trend consists in a linear regression of both temperatures.

	Slope (ºC / year)	Slope (years / ºC)
City temperature	~ 0.0086	~ 116.7116
Global temperature	~ 0.0080	~ 124.6363
Absolute difference	0.0005447855984791923 or **5.45 x 10^(-4)**	

Correlation coefficient

The very small difference in the slope of the trends for both measures leads to a expectation about the **Pearson's correlation coefficient** being high. This can be verified by the following method, still using the moving averages:

```
df['global_temp_10y_MA'].corr(df['city_temp_10y_MA'],
 method = "pearson")
 = 0.9677548684994313
```

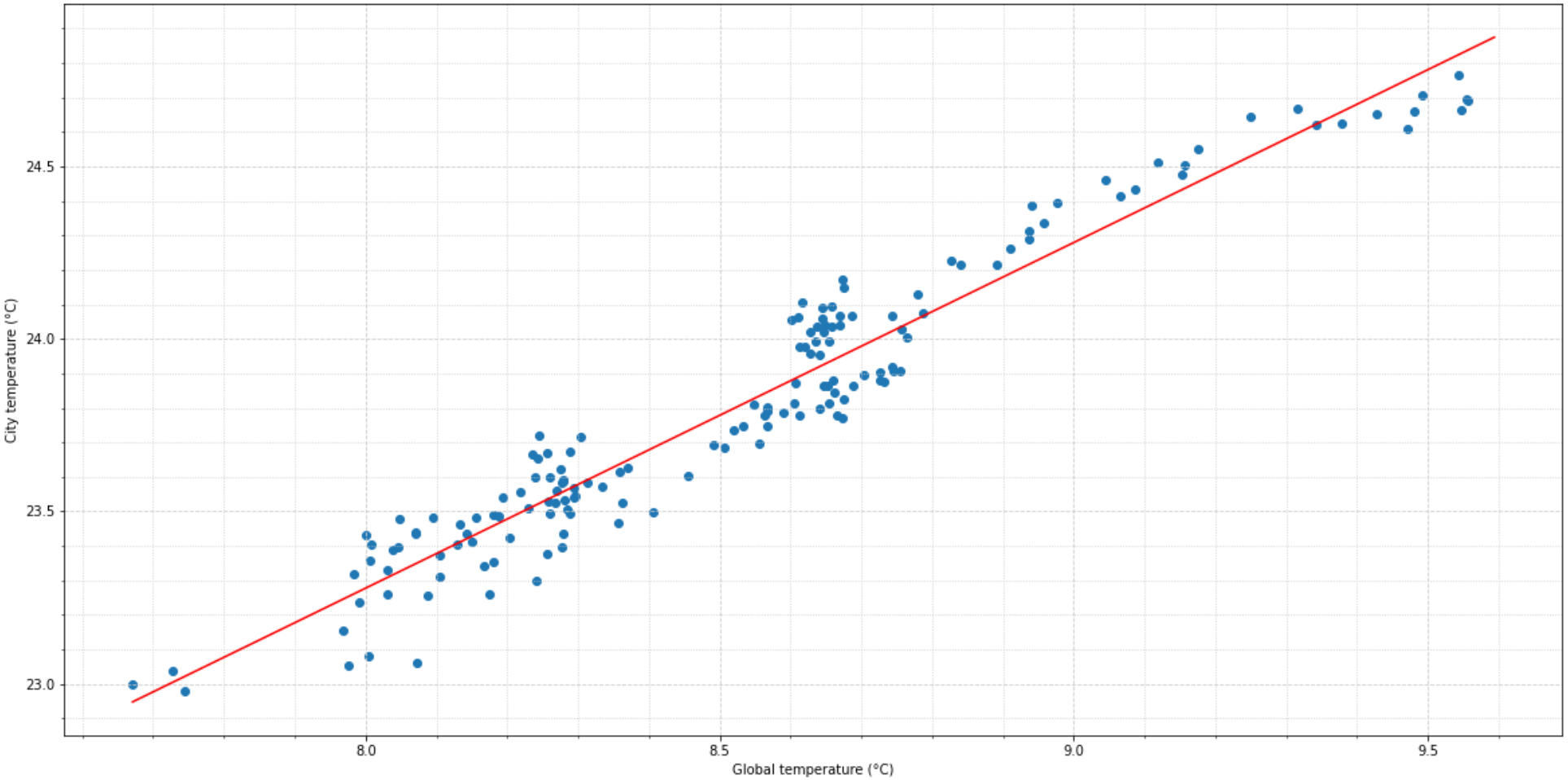
It confirms that the temperatures of the city of Rio de Janeiro and the temperature presented as global temperature are highly bind in a correlational way.

Linear Regression on temperature relation

Using this high correlation, despite of the cause, it's possible to predict with a certain level of accuracy for a still basic analysis. As in order to perform a linear regression using Numpy, it's mandatory to consider only the non-null values of the moving averages.

```
mask = np.isfinite(y_city_MA) & np.isfinite(y_global_MA)
slope,interception = np.polyfit(y_global_MA[mask], y_city_MA[mask],
deg = 1)
reg = slope,interception
trend = np.polyval(reg, y_global_MA)
```

The visualization of this linear regressions is show as follow:


City temperature (°C)
24.5
24.0
23.5
23.0
8.0
8.5
9.0
9.5
Global temperature (°C)

The linear equation that represents this regression is:

```
City temperature = 1.0021917554158453 * years + 15.259902131042605
```

Meaning that for each degree Celsius increase in global temperature, `1.0021917554158453` degree Celsius is increased in Rio de Janeiro temperature, keeping a difference of `15.259902131042605` deg ree Celsius between them.

Once defined a linear equation that represents data with a high correlation, it can be used to perform a basic predictable analysis – disregarding further technical rigor.

Creating the function below and applying an higher value to it, one can get the temperature in the Rio d e Janeiro city based in the global temperature.

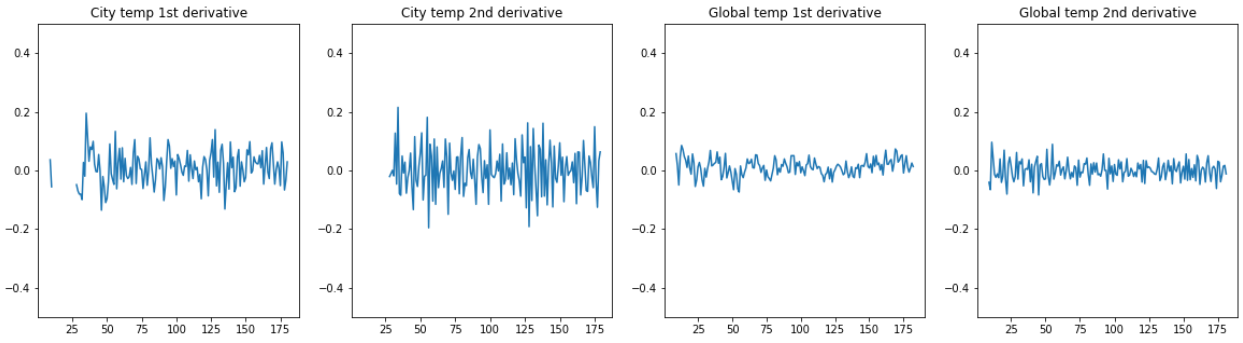
```
def rio_temp (temp_global):
    return slope*temp_global + interception


rio_temp(30)
# 45.32565479351796
```

Derivative analysis

Given the current context of more concern around the human responsibility in climate changes, a valid analysis would be to verify any increment of temperature increase rate after some point in time.

From calculus, the temperature change rate on time can be related to the concept of first derivative of the temperature(year) function. So, any behavior variation on that first derivative would be captured calculating it's derivative (the second derivative of temperature(year) function).

Below are printed the first and second derivative of Rio de Janeiro temperature over the years and the analog measures for Global temperature. The values in x axis represent the number of the measurement, not the year of the measurement.



As can be observed, at no point in time the second derivatives explicitly show a relevant increase. For the data gathered and shown, it's uncertain to estimate any increase in global or local temperature due to human action.