In [1]:
```
import matplotlib.pyplot as plt
import pandas as pd
```

Udacity Data Analyst Nanodegree

Project: Explore Weather Trends

Introduction

For the "Explore Weather Trends" project I've decided to use Python, pandas and Jupyter because I'm already somewhat familiar with them and because everything I need (and much more) is provided by the frameworks.

The `global_data` and `city_data` tables were dumpled from Udacity's SQL workspace, downloaded in CSV format and then zipped. I chose to zip the files because I'm going to host this notebook and all related materials on a GitHub repository.

I've chosen the city of Córdoba, Argentina as the focus of the analysis, alongside another city in the southern hemisphere (Melbourne, Australia) and two in the northern hemisphere (Dallas, United States and Baghdad, Iraq).

Load data

In [2]:
```
global_data_df = pd.read_csv("data/global_data.csv.zip", compression="zip
```

In [3]:
```
global_data_df.head()
```

Out[3]:

year	avg_temp
1750	8.72
1751	7.98
1752	5.78
1753	8.39
1754	8.47

In [4]:
```
city_data_df = pd.read_csv("data/city_data.csv.zip", compression="zip")
```

In [5]:
```
city_data_df.head()
```

Out[5]:

	year	city	country	avg_temp
0	1849	Abidjan	Côte D'Ivoire	25.58
1	1850	Abidjan	Côte D'Ivoire	25.52
2	1851	Abidjan	Côte D'Ivoire	25.67
3	1852	Abidjan	Côte D'Ivoire	NaN
4	1853	Abidjan	Côte D'Ivoire	NaN

In [6]:
```
argentina_data_df = city_data_df[city_data_df.country == "Argentina"]
```

In [7]:
```
argentina_data_df.head()
```

Out[7]:

	year	city	country	avg_temp
16995	1855	Cordoba	Argentina	14.00
16996	1856	Cordoba	Argentina	16.23
16997	1857	Cordoba	Argentina	16.54
16998	1858	Cordoba	Argentina	16.22
16999	1859	Cordoba	Argentina	16.79

In [8]:
```
argentina_data_df.city.unique()  # Only Córdoba and Rosario are available
```

Out[8]:
```
array(['Cordoba', 'Rosario'], dtype=object)
```

In [9]:
```
cordoba_data_df = city_data_df[(city_data_df.city == "Cordoba") & (city_d
```

In [10]:
```
cordoba_data_df.head()
```

Out[10]:

	city	country	avg_temp
year			
1855	Cordoba	Argentina	14.00
1856	Cordoba	Argentina	16.23
1857	Cordoba	Argentina	16.54
1858	Cordoba	Argentina	16.22
1859	Cordoba	Argentina	16.79

In [11]:
```
melbourne_data_df = city_data_df[(city_data_df.city == "Melbourne") & (ci
dallas_data_df = city_data_df[(city_data_df.city == "Dallas") & (city_dat
baghdad_data_df = city_data_df[(city_data_df.city == "Baghdad") & (city_d
```

Computing moving avergages

I've used pandas' `DataFrame.rolling` and `Series.mean` to compute the moving averages as doing it manually would have certainly been cumbersome and error-prone.

I only had yearly temperature averages, so any winodws would have to be larger than that. I chose 5, 25 and 50 year windows to see if I could make different observations based on the window sizes.

In [12]:
```
for window in (5, 25, 50):
    cordoba_data_df[f"mean_{window}yrs"] = cordoba_data_df["avg_temp"].ro
    melbourne_data_df[f"mean_{window}yrs"] = melbourne_data_df["avg_temp"
    dallas_data_df[f"mean_{window}yrs"] = dallas_data_df["avg_temp"].roll
    baghdad_data_df[f"mean_{window}yrs"] = baghdad_data_df["avg_temp"].ro
    global_data_df[f"mean_{window}yrs"] = global_data_df["avg_temp"].roll
```

In [13]:
```
cordoba_data_df.head(20)
```

Out[13]:

year	city	country	avg_temp	mean_5yrs	mean_25yrs	mean_50yrs
1855	Cordoba	Argentina	14.00	NaN	NaN	NaN
1856	Cordoba	Argentina	16.23	NaN	NaN	NaN
1857	Cordoba	Argentina	16.54	NaN	NaN	NaN
1858	Cordoba	Argentina	16.22	NaN	NaN	NaN
1859	Cordoba	Argentina	16.79	15.956	NaN	NaN
1860	Cordoba	Argentina	16.45	16.446	NaN	NaN
1861	Cordoba	Argentina	16.27	16.454	NaN	NaN
1862	Cordoba	Argentina	16.32	16.410	NaN	NaN
1863	Cordoba	Argentina	15.86	16.338	NaN	NaN
1864	Cordoba	Argentina	16.35	16.250	NaN	NaN
1865	Cordoba	Argentina	16.89	16.338	NaN	NaN
1866	Cordoba	Argentina	16.68	16.420	NaN	NaN
1867	Cordoba	Argentina	16.42	16.440	NaN	NaN
1868	Cordoba	Argentina	16.73	16.614	NaN	NaN
1869	Cordoba	Argentina	16.34	16.612	NaN	NaN
1870	Cordoba	Argentina	16.34	16.502	NaN	NaN
1871	Cordoba	Argentina	16.01	16.368	NaN	NaN
1872	Cordoba	Argentina	16.21	16.326	NaN	NaN
1873	Cordoba	Argentina	16.34	16.248	NaN	NaN
1874	Cordoba	Argentina	15.62	16.104	NaN	NaN

In [14]:
```
global_data_df.head(20)
```

Out[14]:

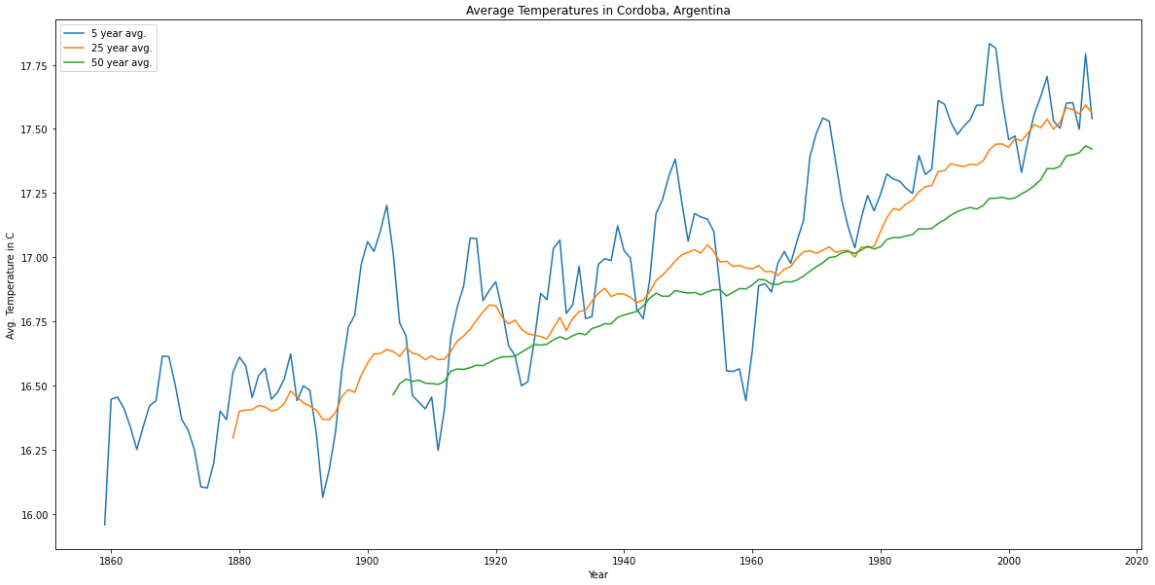
year	avg_temp	mean_5yrs	mean_25yrs	mean_50yrs
1750	8.72	NaN	NaN	NaN
1751	7.98	NaN	NaN	NaN
1752	5.78	NaN	NaN	NaN
1753	8.39	NaN	NaN	NaN
1754	8.47	7.868	NaN	NaN
1755	8.36	7.796	NaN	NaN
1756	8.85	7.970	NaN	NaN
1757	9.02	8.618	NaN	NaN
1758	6.74	8.288	NaN	NaN
1759	7.99	8.192	NaN	NaN
1760	7.19	7.958	NaN	NaN
1761	8.77	7.942	NaN	NaN
1762	8.61	7.860	NaN	NaN
1763	7.50	8.012	NaN	NaN
1764	8.40	8.094	NaN	NaN
1765	8.25	8.306	NaN	NaN
1766	8.41	8.234	NaN	NaN
1767	8.22	8.156	NaN	NaN
1768	6.78	8.012	NaN	NaN
1769	7.69	7.870	NaN	NaN

Plotting the data

I used `matplotlib` to generate the charts, following the suggestions from this blog post.

In [15]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot()
ax.set_xlabel("Year")
ax.set_ylabel("Avg. Temperature in C")
ax.set_title("Average Temperatures in Cordoba, Argentina")
ax.plot(cordoba_data_df.mean_5yrs)
ax.plot(cordoba_data_df.mean_25yrs)
ax.plot(cordoba_data_df.mean_50yrs)
ax.legend(["5 year avg.", "25 year avg.", "50 year avg."])
```

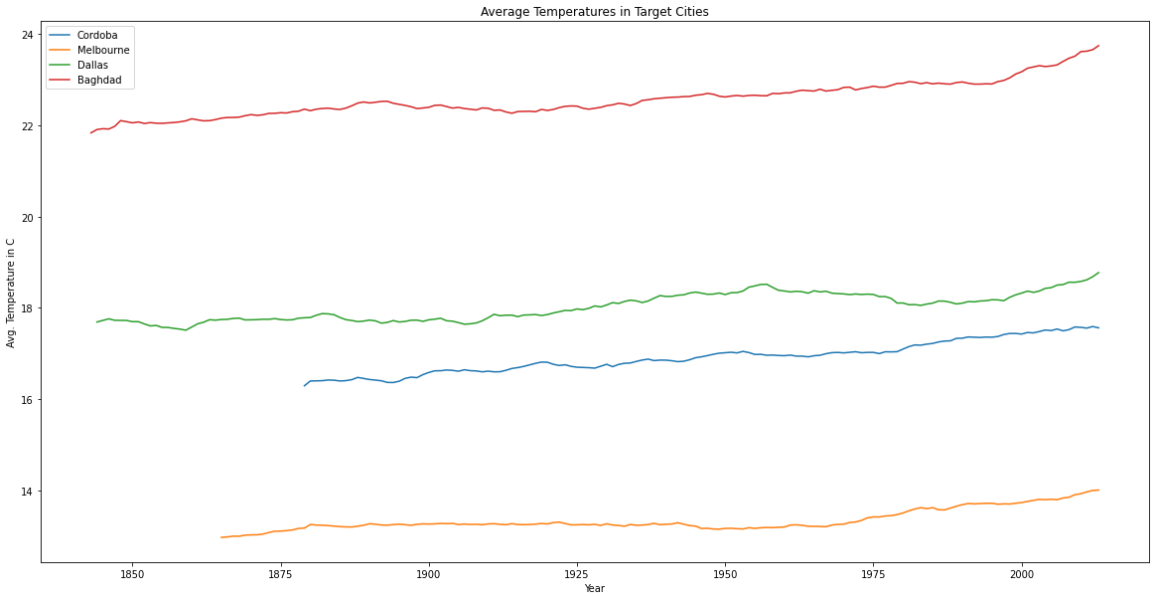
Out[15]:
```
<matplotlib.legend.Legend at 0x7f70f4156ec0>
```



This chart clearly shows that moving averages smooth (as mentioned in the lesson) out the curves making it easy to observe potential trends in the data. In this case, the 50 year average curve shows a clear upward trend in average temperature.

In [16]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot()
ax.set_xlabel("Year")
ax.set_ylabel("Avg. Temperature in C")
ax.set_title("Average Temperatures in Target Cities")
ax.plot(cordoba_data_df.mean_25yrs)
ax.plot(melbourne_data_df.mean_25yrs)
ax.plot(dallas_data_df.mean_25yrs)
ax.plot(baghdad_data_df.mean_25yrs)
ax.legend(["Cordoba", "Melbourne", "Dallas", "Baghdad"])
```

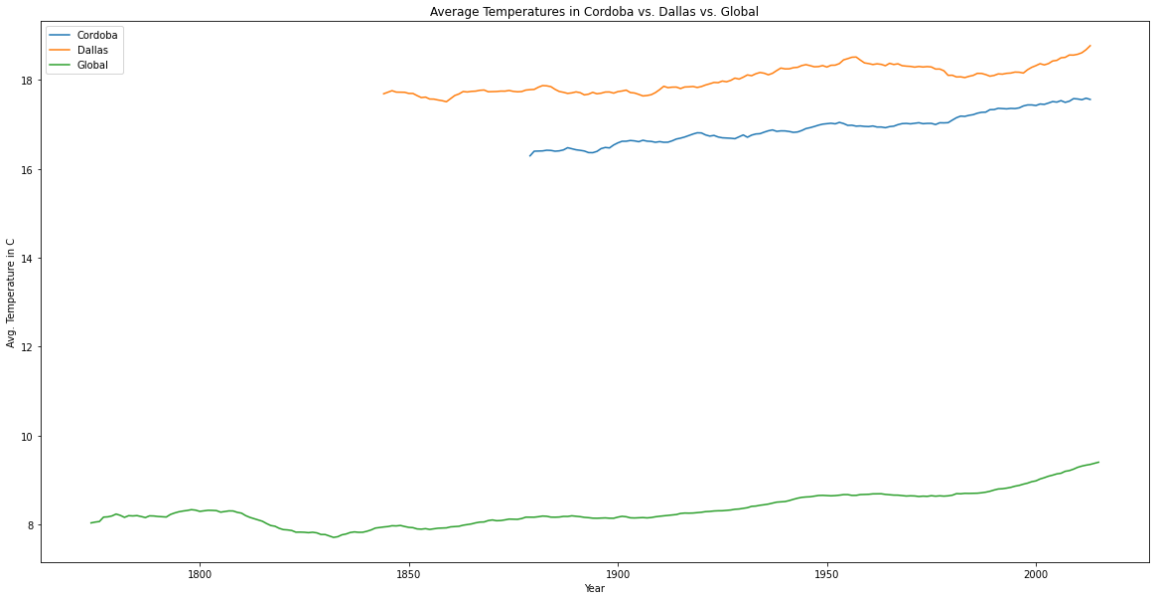
Out[16]:
```
<matplotlib.legend.Legend at 0x7f70f1e511b0>
```



The upwards trend is harder to see now (but it's there), but what's interesting about this chart are the clear similarities between Cordoba and Dallas (similar latitudes and climates, both landlocked) and their differences with Melbourne (coastal city) and Baghdad (straight up desert).

In [17]:
```
fig = plt.figure(figsize=(20, 10))
ax = fig.add_subplot()
ax.set_xlabel("Year")
ax.set_ylabel("Avg. Temperature in C")
ax.set_title("Average Temperatures in Cordoba vs. Dallas vs. Global")
ax.plot(cordoba_data_df.mean_25yrs)
ax.plot(dallas_data_df.mean_25yrs)
ax.plot(global_data_df.mean_25yrs)
ax.legend(["Cordoba", "Dallas", "Global"])
```

Out[17]:
```
<matplotlib.legend.Legend at 0x7f70f1e990c0>
```



The upwards trend since 1900 is somewhat clear, and we can see that Cordoba follows the trend of the global average. Once again I used pandas to get the correlation coefficient between Cordoba's and the global yearly averages, which clearly shows a correlation

In [18]:
```
cordoba_data_df.avg_temp.corr(global_data_df.avg_temp)
```

Out[18]:
```
0.5793453951587677
```

The value is similar to the correlation coefficient between Dallas' and the global yearly avergages:

In [19]:
```
dallas_data_df.avg_temp.corr(global_data_df.avg_temp)
```

Out[19]:
```
0.5737218176756127
```

However, Cordoba's and Dallas' data are not so strongly correlated:

In [20]:
```
cordoba_data_df.avg_temp.corr(dallas_data_df.avg_temp)
```

Out[20]:
```
0.22637709501776718
```

In [ ]:
```

```