Project - Exploring weather trends

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Tooling

The following programming languages and tools are used in this project:

- MySQL and SQL
- Jupyter notebook and python
- Libraries: pandas, matplotlib

Project instructions

source: Udacity nanodegree project description

Your goal will be to create a visualization and prepare a write up describing the similarities and differences between global temperature trends and temperature trends in the closest big city to where you live. To do this, you'll follow the steps below:

- Extract the data from the database. There's a workspace in the next section that is connected to a database. You'll need to export the temperature data for the world as well as for the closest big city to where you live. You can find a list of cities and countries in the city_list table. To interact with the database, you'll need to write a SQL query.

  - Write a SQL query to extract the city level data. Export to CSV.
  - Write a SQL query to extract the global data. Export to CSV.
- Open up the CSV in whatever tool you feel most comfortable using. We suggest using Excel or Google sheets, but you are welcome to use another tool, such as Python or R.
- Create a line chart that compares your city's temperatures with the global temperatures. Make sure to plot the moving average rather than the yearly averages in order to smooth out the lines, making trends more observable (the last concept in the previous lesson goes over how to do this in a spreadsheet).
- Make observations about the similarities and differences between the world averages and your city's averages, as well as overall trends. Here are some questions to get you started.
  - Is your city hotter or cooler on average compared to the global average? Has the difference been consistent over time?
  - "How do the changes in your city's temperatures over time compare to the changes in the global average?"
  - What does the overall trend look like? Is the world getting hotter or cooler? Has the trend been consistent over the last few hundred years?

Exploring weather trends

Fetching the data

In order to fetch the data from the database, the following needs to be established:

- a database containing the data has to exist.
  - if the database is not set, run the helper python script `setup_db.py` in `/data` which uses the exported data found in `.csv` to set it up
- create a connection to the database (in our case we used a MySQL database)
- define SQL queries for fetching the data
- run the SQL queries and load them into proper format (here we used Pandas DataFrames)
- alternatively, the data can be directly loaded from the exported `.csv` files - jump directly to Fetching the data from the CSV files

Creating a MySQL connection to the existing database named 'mydatabase'

In [14]:
```
import MySQLdb

db_host = 'localhost'
db_username = 'root'
db_password = 'password'
db_name = 'mydatabase'

mysql_conn = MySQLdb.connect(host = db_host,
                             user = db_username,
                             passwd= db_password,
```

```
                        db = db_name)

if (mysql_conn):
    # connection succesful
    print("Successfully connected to '%s/%s'" % (db_host, db_name))
else:
    # connection unsuccesful
    print("Connection unsuccessful")
```

```
Successfully connected to 'localhost/mydatabase'
```

SQL queries for fetching the data

SQL query for fetching the `global_data`

```sql
SELECT * FROM global_data
```

SQL query for fetching all `city_data`

```sql
SELECT * FROM city_data
```

or for a specific city, e.g.

```sql
SELECT * FROM city_data
WHERE city = 'Munich'
```

(optional) SQL query for fetching the `city_list` data

```sql
SELECT * FROM city_list
```

In [15]:

```
# define SQL queries
global_data_sql_query = "SELECT * from global_data"
city_data_sql_query = "SELECT * from city_data"
city_list_sql_query = "SELECT * from city_list"
```

Fetching the data from the database using SQL queries

In [16]:

```
import pandas as pd

# load the data from the db into panda Dataframes
global_data = pd.read_sql_query(global_data_sql_query, mysql_conn)
city_data = pd.read_sql_query(city_data_sql_query, mysql_conn)
city_list = pd.read_sql_query(city_list_sql_query, mysql_conn)

print("Loaded a dataframe with %s records" % len(global_data))
print("Loaded a dataframe with %s records" % len(city_data))
print("Loaded a dataframe with %s records" % len(city_list))

mysql_conn.close()
```

```
Loaded a dataframe with 266 records
Loaded a dataframe with 71311 records
Loaded a dataframe with 345 records
```

Fetching the data from the CSV files

Alternatively, the data can be directly loaded from the `.csv` files, if available.

In [17]:

```
global_data_csv = pd.read_csv('data/global_data.csv')
city_data_csv = pd.read_csv('data/city_data.csv')
city_list_csv = pd.read_csv('data/city_list.csv')
```

A simple sanity check confirms the data being loaded from the database and the CSV files is the same

In [18]:
```
city_data.info()
city_data_csv.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71311 entries, 0 to 71310
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   year      71311 non-null  int64
 1   city      71311 non-null  object
 2   country   71311 non-null  object
 3   avg_temp  68764 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 2.2+ MB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71311 entries, 0 to 71310
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   year      71311 non-null  int64
 1   city      71311 non-null  object
 2   country   71311 non-null  object
 3   avg_temp  68764 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 2.2+ MB
```

Either way of obtaining the data works.

Exploring the data

Once the data is fetched from the database/other data formats, some basic checks on the obtained data can performed such as checking the size, or checking for missing values to understand what is it that are having as an input.

`city_list` data

Let's start with the simplest data `city_list`

In [19]:
```
city_list.head()
```

Out[19]:

	city	country
0	Abidjan	Côte D'Ivoire
1	Abu Dhabi	United Arab Emirates
2	Abuja	Nigeria
3	Accra	Ghana
4	Adana	Turkey

As it can be seen, the data contains rows with a unique ID and corresponding city and country pair.

As we will later see, `global_data` contains exactly the same information so there is no specific usage of this dataset except for an easier/quicker check if the city of our interest is contained in the database at all.

In [20]:
```
city_list[city_list["city"] == "Munich"]
```

Out[20]:

	city	country
214	Munich	Germany

which is equivalent to the SQL query

```
SELECT * FROM city_list
WHERE city = 'Munich'
```

As it can be seen, the city our interest is contained in the dataset and we can peform with the analysis.

Furthermore, we can easily check some other cities in Germany which could also be used for the comparison.

In [21]:
```
city_list[city_list["country"] == "Germany"]
```

Out[21]:

	city	country
42	Berlin	Germany
113	Hamburg	Germany
214	Munich	Germany

`global_data` data

Then, let us check what is contained the `global_data` dataset.

In [22]:
```
global_data.head()
```

Out[22]:

	year	avg_temp
0	1750	8.72
1	1751	7.98
2	1752	5.78
3	1753	8.39
4	1754	8.47

As it can be seen above, we again have rows of data containing an unique ID and pairs of years and average temperature in °C.

Let us see some min, max values of each.

In [23]:
```
print('Year ranges:')
print('min(global_data[year]) = %s' % min(global_data['year']))
print('max(global_data[year]) = %s' % max(global_data['year']))

print('\nAverage temperature ranges:')
```

```
print('min(global_data[avg_temp]) = %s °C' % min(global_data['avg_temp']))
print('max(global_data[avg_temp]) = %s °C' % max(global_data['avg_temp']))
```

```
Year ranges:
min(global_data[year]) = 1750
max(global_data[year]) = 2015

Average temperature ranges:
min(global_data[avg_temp]) = 5.78 °C
max(global_data[avg_temp]) = 9.83 °C
```

Taking a look above, `global_data` contains average temperatures for years ranging from 1750 up to 2015.

At the end, let us do a simple check to verify we have an entry of `avg_temp` for each of the corresponding year.

In [24]:
```
print("There are %s entries of global temperature averages in 'global_data'
print("Among those, %s are NaN" % global_data['avg_temp'].isna().sum())
```

```
There are 266 entries of global temperature averages in 'global_data'
Among those, 0 are NaN
```

`city_data` data

Lastly, let us quickly take a look what is contained in `city_data` .

In [25]:
```
city_data.head()
```

Out[25]:

	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

As expected, `city_data` contains entries containing a year, city, country and average temperatures values.

From the first look, it appears that some values are empty.

In [26]:
```
city_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 71311 entries, 0 to 71310
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   year      71311 non-null  int64  
 1   city      71311 non-null  object 
 2   country   71311 non-null  object 
 3   avg_temp  68764 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 2.2+ MB
```

Let us focus on our point of interest and select all temperatures for Munich

In [27]:
```
munich_data = city_data[city_data["city"] == "Munich"].copy()
munich_data.head()
```

Out[27]:

	year	city	country	avg_temp
43994	1743	Munich	Germany	1.32
43995	1744	Munich	Germany	6.09
43996	1745	Munich	Germany	-2.15
43997	1746	Munich	Germany	NaN
43998	1747	Munich	Germany	NaN

In [28]:
```
print("There are %s entries for Munich in 'city_data'" % len(munich_data['y
print("Among those, %s are NaN" % munich_data['avg_temp'].isna().sum())
```

```
There are 271 entries for Munich in 'city_data'
Among those, 4 are NaN
```

As it can be seen above, out of 271 entries for Munich, we have 4 that are empty.

In [29]:
```
munich_data[munich_data["avg_temp"].isna()]
```

Out[29]:

	year	city	country	avg_temp
43997	1746	Munich	Germany	NaN
43998	1747	Munich	Germany	NaN
43999	1748	Munich	Germany	NaN
44000	1749	Munich	Germany	NaN

We can visually see that the missing data is for the years 1746-1749.

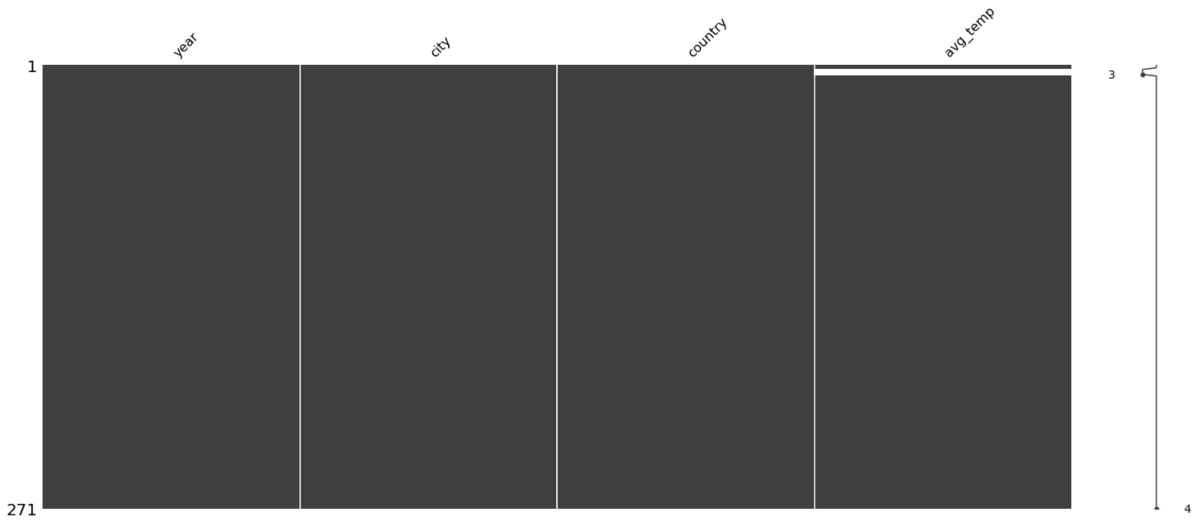
In [30]:
```
print('Year ranges:')
print('min(munich_data[year]) = %s' % min(munich_data['year']))
print('max(munich_data[year]) = %s' % max(munich_data['year']))

print('\nAverage temperature ranges:')
print('min(munich_data[avg_temp]) = %s °C' % min(munich_data['avg_temp']))
print('max(munich_data[avg_temp]) = %s °C' % max(munich_data['avg_temp']))
```

```
Year ranges:
min(munich_data[year]) = 1743
max(munich_data[year]) = 2013

Average temperature ranges:
min(munich_data[avg_temp]) = -2.15 °C
max(munich_data[avg_temp]) = 6.64 °C
```

In addition to containing empty values for years 1746-1749, the last recorded year of the Munich dataset is 2013, in contrast to 2015 for global average temparature.

We can also visualize the missing values using the `missigno` library.

In [31]:
```
import missingno as miss

miss.matrix(munich_data);
```



As the limitted data for years 1746-1749 years is available, for simplicity we will just reduce the scope of our analysis for the range from 1750 to 2015 as it will not have a great impact on the analysis.

In [32]:

```
range_start = 1750
range_end = 2015

# remove the unnecessary data beyond the range
munich_data = munich_data.loc[(munich_data.year >= range_start) & (munich_d
global_data = global_data.loc[(global_data.year >= range_start) & (global_d
```

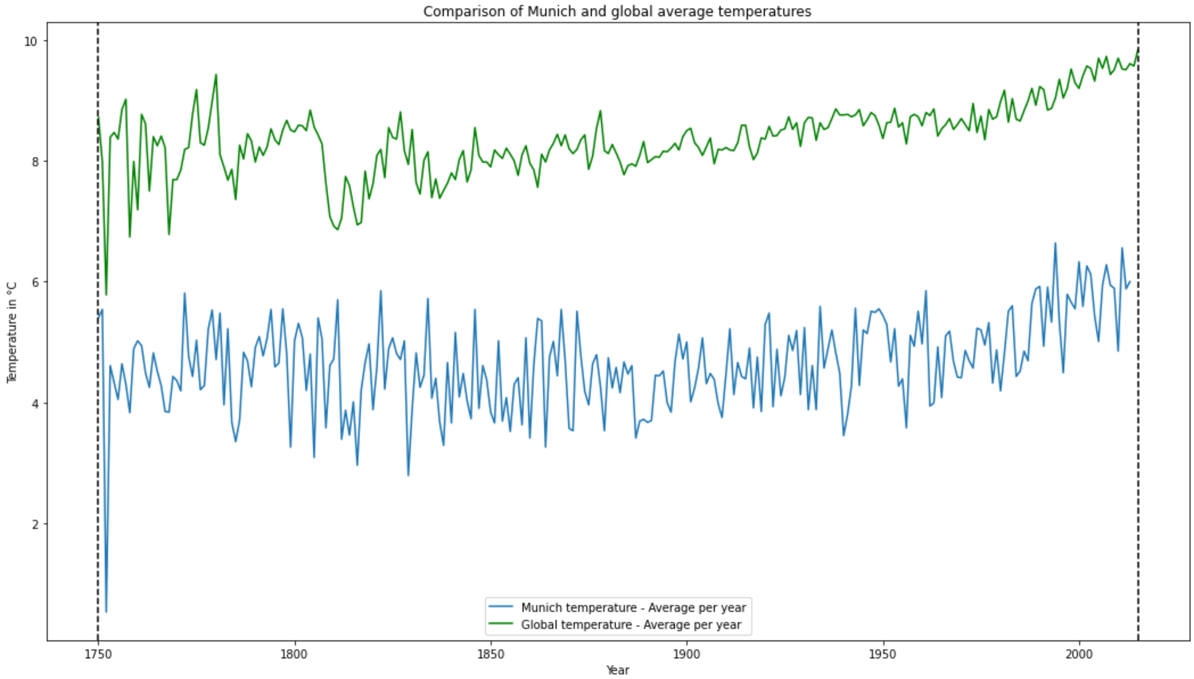
Plotting the data

Average temperatures of Munich vs global

For the start, let us simply plot the raw Munich and global temperatures data. Furthermore, let us denote the range of years we shall focus the analysis on.

In [33]:

```
import matplotlib.pyplot as plt

plt.rcParams['figure.figsize'] = [18, 10]
ax = plt.gca()

munich_data.plot(x="year", y="avg_temp", ax=ax)
global_data.plot(x="year", y="avg_temp", color='green', ax=ax)

plt.axvline(x=range_start, ymin=0, ymax=1, color='black', linestyle='--')
plt.axvline(x=range_end, ymin=0, ymax=1, color='black', linestyle='--')

plt.title('Comparison of Munich and global average temperatures')
plt.xlabel("Year");
plt.ylabel("Temperature in °C");
plt.legend(["Munich temperature - Average per year",
           "Global temperature - Average per year",
          ]);
```



Moving average temperatures

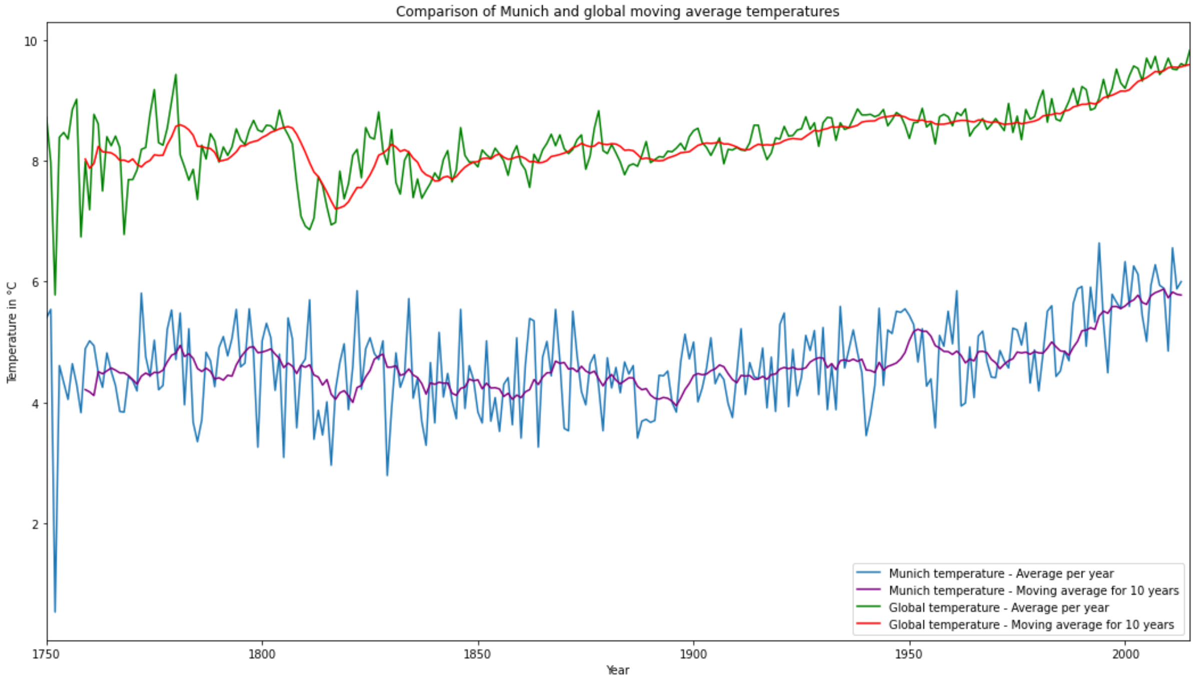
As seen above, the yearly averages differ significantly between different years. To make temperature trends more observable, let us calculate the moving averages to smoothen out the lines.

In [34]:

```
moving_avg_year_range = 10 # in years

munich_data["moving_avg_temp"] = munich_data["avg_temp"].rolling(window = m
global_data["moving_avg_temp"] = global_data["avg_temp"].rolling(window = m
```

In [35]:

```
plt.rcParams['figure.figsize'] = [18, 10]
ax = plt.gca()

munich_data.plot(x="year", y="avg_temp", ax=ax)
munich_data.plot(kind='line',x='year',y='moving_avg_temp', color='purple',

global_data.plot(x="year", y="avg_temp", color='green', ax=ax)
global_data.plot(kind='line',x='year',y='moving_avg_temp', color='red', ax=

plt.xlim(range_start, range_end)
plt.title('Comparison of Munich and global moving average temperatures')
plt.xlabel("Year");
plt.ylabel("Temperature in °C");
ax.legend(["Munich temperature - Average per year",
           "Munich temperature - Moving average for 10 years",
           "Global temperature - Average per year",
           "Global temperature - Moving average for 10 years",
          ]);
```



Difference between moving average temperatures to global

In [36]:

```
moving_avg_temp_diff = munich_data[munich_data['year'] > range_start+moving

# remove unnecessary columns, keep only year and moving_avg_temp
moving_avg_temp = moving_avg_temp_diff.loc[: , [True, False, False, False, '

# reset index so that it goes from 0
moving_avg_temp = moving_avg_temp.reset_index(drop=True)

#rename column
moving_avg_temp  = moving_avg_temp.rename({'moving_avg_temp':'munich_moving

# add global_moving_avg_temp
global_moving_avg_temp = global_data[global_data['year'] > range_start+movi
global_moving_avg_temp = global_moving_avg_temp.loc[: , [False, False, True
global_moving_avg_temp = global_moving_avg_temp.reset_index(drop=True)

# add to the original DataFrame
moving_avg_temp['global_moving_avg_temp'] = global_moving_avg_temp

# calculate the difference between Munich and global temperatures
moving_avg_temp['diff_to_global'] = moving_avg_temp['global_moving_avg_temp

moving_avg_temp.head()
```

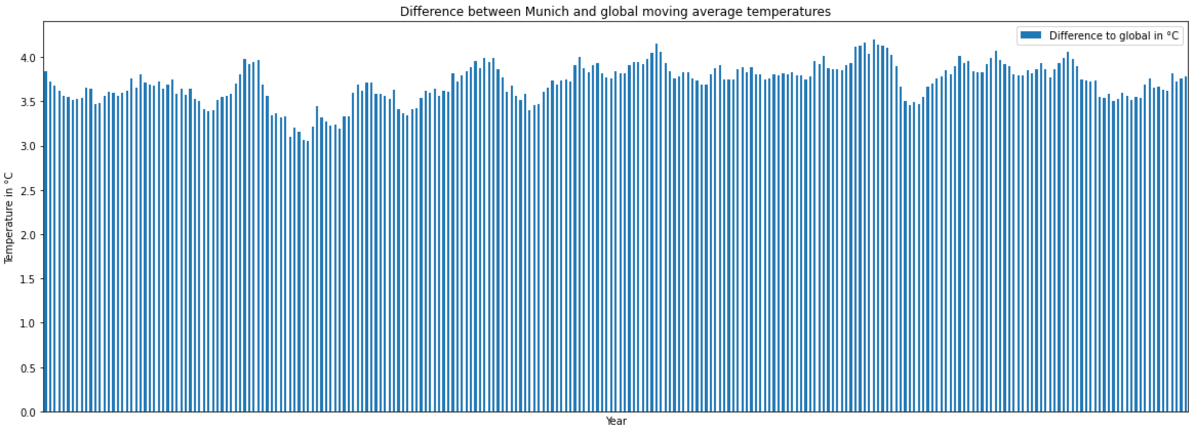
Out[36]:

	year	munich_moving_avg_temp	global_moving_avg_temp	diff_to_global
0	1761	4.114	7.956	3.842
1	1762	4.510	8.239	3.729
2	1763	4.474	8.150	3.676
3	1764	4.523	8.143	3.620
4	1765	4.570	8.132	3.562

In [37]:

```
ax = moving_avg_temp.plot(x="year", y="diff_to_global", kind='bar', figsize
ax.set_xticks([])
ax.set_xlabel("Year");
```

```
ax.set_ylabel("Temperature in °C");
ax.legend(["Difference to global in °C"]);
```



Linear regression

We can perform linear regression to define a model/a function best explaining our data. Year to global and Munich average temperatures data can be used for fitting and deducting a simple 1st linear function.

Firstly we will fit the data for all year ranges from 1750. Then we will focus on the data from 1900 and 1970 to make the fit more suitable for the trends evident in the data.

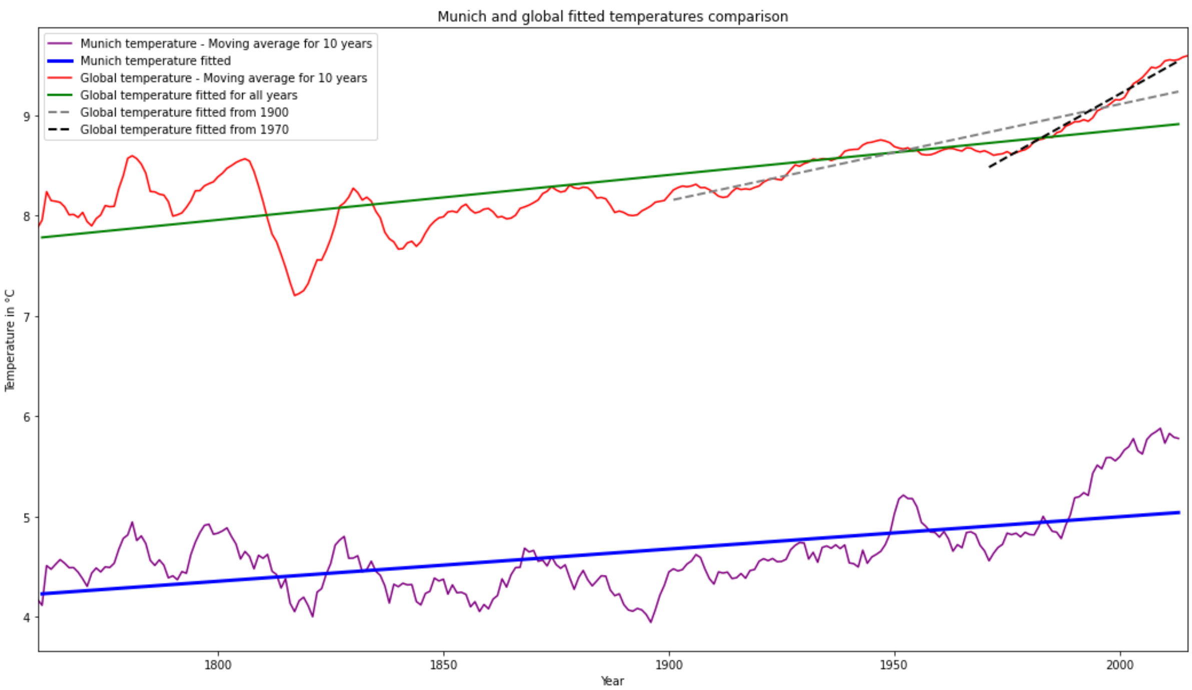
In [38]:

```
import numpy as np

order = 1

# Munich data
munich_fit = np.polyfit(moving_avg_temp['year'], moving_avg_temp['munich_mo
munich_temp_fit_func = np.poly1d(munich_fit)

munich_fit_history_fit = munich_temp_fit_func(moving_avg_temp['year'].to_nu

munich_fit_history = pd.DataFrame(moving_avg_temp['year'], columns=['year']
munich_fit_history['fit'] = munich_fit_history_fit

# global data
global_fit = np.polyfit(moving_avg_temp['year'], moving_avg_temp['global_mo
global_temp_fit_func = np.poly1d(global_fit)

global_fit_history_fit = global_temp_fit_func(moving_avg_temp['year'].to_nu

global_fit_history = pd.DataFrame(moving_avg_temp['year'], columns=['year']
global_fit_history['fit'] = global_fit_history_fit

# from 1900

# global data
fit_year_start = 1900
x_input = moving_avg_temp[moving_avg_temp['year']>fit_year_start]['year']
y_input = moving_avg_temp[moving_avg_temp['year']>fit_year_start]['global_m
global_fit_last_100 = np.polyfit(x_input, y_input, order)
global_temp_fit_func_last_100 = np.poly1d(global_fit_last_100)

global_fit_history_fit_last_100 = global_temp_fit_func_last_100(moving_avg_
global_fit_history_last_100 = pd.DataFrame(moving_avg_temp[moving_avg_temp[
global_fit_history_last_100['fit'] = global_fit_history_fit_last_100
```

```
# from 1970
fit_year_start = 1970
x_input = moving_avg_temp[moving_avg_temp['year']>fit_year_start]['year']
y_input = moving_avg_temp[moving_avg_temp['year']>fit_year_start]['global_m
global_fit_last_50 = np.polyfit(x_input, y_input, order)
global_temp_fit_func_last_50 = np.poly1d(global_fit_last_50)

global_fit_history_fit_last_50 = global_temp_fit_func_last_50(moving_avg_te
global_fit_history_last_50 = pd.DataFrame(moving_avg_temp[moving_avg_temp['
global_fit_history_last_50['fit'] = global_fit_history_fit_last_50
```

In [39]:

```
plt.rcParams['figure.figsize'] = [18, 10]
ax = plt.gca()

munich_data.plot(x="year", y="moving_avg_temp", color='purple', ax=ax)
munich_fit_history.plot(x="year", y="fit", color='blue', linewidth=3.0, ax=

ax = global_data.plot(x="year", y="moving_avg_temp", color='red', ax=ax)
ax = global_fit_history.plot(x="year", y="fit", color='green', linewidth=2.

ax = global_fit_history_last_100.plot(x="year", y="fit", color='gray', line
ax = global_fit_history_last_50.plot(x="year", y="fit", color='black', line

plt.title('Munich and global fitted temperatures comparison')
plt.xlim(range_start+moving_avg_year_range, range_end)
ax.set_xlabel("Year");
ax.set_ylabel("Temperature in °C");
ax.legend(["Munich temperature - Moving average for 10 years",
           "Munich temperature fitted",
           "Global temperature - Moving average for 10 years",
           "Global temperature fitted for all years",
           "Global temperature fitted from 1900",
           "Global temperature fitted from 1970",
          ]);
```



Temperature prediction

Having performed a simple linear regression, we deducted a 1st order linear function describing the data. The function can be then straightforwardly used to predict the future trends.

In [40]:

```
# using the fitted data for all years

# temperature in 2050
prediction_year = 2050
print(f'Predicted global average temperature in 2050 will be {global_temp_f
print(f'Predicted Munich average temperature in 2050 will be {munich_temp_f

# temperature in 2100
prediction_year = 2100
print(f'Predicted global average temperature in 2100 will be {global_temp_f
print(f'Predicted Munich average temperature in 2100 will be {munich_temp_f

# using the fitted data from 1900
print(f'Predicted global average temperature in 2050 using trends from 1900
print(f'Predicted global average temperature in 2100 using trends from 1900

# using the fitted data from 1970
print(f'Predicted global average temperature in 2050 using trends from 1970
print(f'Predicted global average temperature in 2100 using trends from 1970
```

```
Predicted global average temperature in 2050 will be 9.08 °C
Predicted Munich average temperature in 2050 will be 5.16 °C

Predicted global average temperature in 2100 will be 9.30 °C
Predicted Munich average temperature in 2100 will be 5.32 °C

Predicted global average temperature in 2050 using trends from 1900 will be
9.59 °C
Predicted global average temperature in 2100 using trends from 1900 will be
10.08 °C

Predicted global average temperature in 2050 using trends from 1970 will be
10.47 °C
Predicted global average temperature in 2100 using trends from 1970 will be
11.73 °C
```

Analyzing the data

The temperature trends are visually observable. Let us calculate the average temperates of Munich and global and compare them quantitatively.

Average temperature difference

In [41]:

```
avg_temp_munich = munich_data['avg_temp'].mean()
avg_temp_global = global_data['avg_temp'].mean()

print(f'Munich average temperature is {avg_temp_munich:2.2f} °C')
print(f'Global average temperature is {avg_temp_global:2.2f} °C')
print(f'Difference between global and Munich average temperature is {avg_te
```

```
Munich average temperature is 4.64 °C
Global average temperature is 8.37 °C
Difference between global and Munich average temperature is 3.73 °C
```

Correlation

In [42]:

```
from scipy.stats import pearsonr

# calculate Pearson's correlation
```

```
correlation, _ = pearsonr(moving_avg_temp['munich_moving_avg_temp'], moving
print('Pearsons correlation: %.3f' % correlation)
```

```
Pearsons correlation: 0.873
```

The value of 0.873 denotes strong positive correlation between moving average temperatures of Munich and global temperatures.

Observations

Taking all of the analysis above the following can be concluded:

- Munich average temperature of 4.64 °C is lower than the global average temperature of 8.37 °C with a difference of 3.73 °C on average.
- Considering the difference between moving average temperatures to global, the difference between Munich and global temperature has been fairly consistent throughout time ranging from 3.0 to 4.5 °C on particular years.
- The overall trend increases in a positive direction meaning that the global temperature increases with time. Likewise, Munich temperature exhibits the same upward trend.
- The temperature increase is particularly evident in the last 120 years (from 1900) as the increase has been significant.
- As presented in linear regression, taking a look at global temperature trends from 1970, the predicted global average temperature will be 10.47 °C in 2050 and 11.73 °C in 2100.