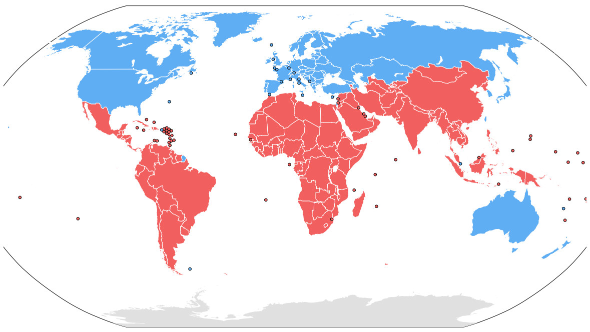
In [1]:

```
# Data Source: https://www.kaggle.com/worldbank/world-development-indicators
# Folder: 'world-development-indicators'
```

Matplotlib: Exploring Data Visualization

World Development Indicators



This week, we will be using an open dataset from [Kaggle (https://www.kaggle.com)](https://www.kaggle.com). It is [The World Development Indicators (https://www.kaggle.com/worldbank/world-development-indicators)](https://www.kaggle.com/worldbank/world-development-indicators) dataset obtained from the World Bank containing over a thousand annual indicators of economic development from hundreds of countries around the world.

This is a slightly modified version of the original dataset from [The World Bank (http://data.worldbank.org/data-catalog/world-development-indicators)](http://data.worldbank.org/data-catalog/world-development-indicators).

List of the [available indicators (https://www.kaggle.com/benhamner/d/worldbank/world-development-indicators/indicators-in-data)](https://www.kaggle.com/benhamner/d/worldbank/world-development-indicators/indicators-in-data) and a [list of the available countries (https://www.kaggle.com/benhamner/d/worldbank/world-development-indicators/countries-in-the-wdi-data)](https://www.kaggle.com/benhamner/d/worldbank/world-development-indicators/countries-in-the-wdi-data).

Step 1: Initial exploration of the Dataset

In [2]:

```
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt
%matplotlib inline

data = pd.read_csv('./world-development-indicators/Indicators.csv')
data.shape
```

Out[2]:

```
(5656458, 6)
```

This is a really large dataset, at least in terms of the number of rows. But with 6 columns, what does this hold?

In [3]:

```
data.head(10)
```

Out[3]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
0	Arab World	ARB	Adolescent fertility rate (births per 1,000 wo...	SP.ADO.TFRT	1960	1.335609e+02
1	Arab World	ARB	Age dependency ratio (% of working-age populat...	SP.POP.DPND	1960	8.779760e+01
2	Arab World	ARB	Age dependency ratio, old (% of working-age po...	SP.POP.DPND.OL	1960	6.634579e+00
3	Arab World	ARB	Age dependency ratio, young (% of working-age ...	SP.POP.DPND.YG	1960	8.102333e+01
4	Arab World	ARB	Arms exports (SIPRI trend indicator values)	MS.MIL.XPRT.KD	1960	3.000000e+06
5	Arab World	ARB	Arms imports (SIPRI trend indicator values)	MS.MIL.MPRT.KD	1960	5.380000e+08
6	Arab World	ARB	Birth rate, crude (per 1,000 people)	SP.DYN.CBRT.IN	1960	4.769789e+01
7	Arab World	ARB	CO2 emissions (kt)	EN.ATM.CO2E.KT	1960	5.956399e+04
8	Arab World	ARB	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1960	6.439635e-01
9	Arab World	ARB	CO2 emissions from gaseous fuel consumption (%...	EN.ATM.CO2E.GF.ZS	1960	5.041292e+00

Looks like it has different indicators for different countries with the year and value of the indicator.

How many UNIQUE country names are there ?

In [4]:

```
countries = data['CountryName'].unique().tolist()
len(countries)
```

Out[4]:

```
247
```

To find put how many 'unique' contries are in the column

Are there same number of country codes ?

In [5]:

```
# How many unique country codes are there ? (should be the same #)
countryCodes = data['CountryCode'].unique().tolist()
len(countryCodes)
```

Out[5]:

```
247
```

If we have 247 countries, we should have 246 country codes. And, we do.

How many indicator we have?

In [6]:

```
# How many unique indicators are there ? (should be the same #)
indicators = data['IndicatorName'].unique().tolist()
len(indicators)
```

Out[6]:

```
1344
```

This is a pretty extensive list of indicators.

How many indicator codes of data do we have ?

In [7]:

```
# How many unique indicator codes are there ? (should be the same #)
indicatorCode = data['IndicatorCode'].unique().tolist()
len(indicatorCode)
```

Out[7]:

```
1344
```

How many years of data do we have ?

In [8]:

```
# How many years of data do we have ?
years = data['Year'].unique().tolist()
len(years)
```

Out[8]:

```
56
```

What's the range of years

In [9]:

```
print(min(years), 'to ', max(years))
```

```
1960 to  2015
```

In short, we have a pretty good feel for the dataset. We've various indicators per country over the time span of 1960 to 2015.

Matplotlib: Basic Plotting, Part 1

Lets pick a country and an indicator to explore: CO2 Emissions per capita and the USA

In [10]:

```
# Select CO2 emissions for the USA
hist_indicator = 'CO2 emissions \(metric' # \( 功能: 只找字串符合 'CO2 emissions (metr
hist_country = 'USA'

mask1 = data['IndicatorName']. str.contains(hist_indicator)
mask2 = data['CountryCode'].str.contains(hist_country)

# stage is just those indicators matching the USA for country code and CO2 emission:
stage = data[mask1 & mask2]
```

In [11]:

```
stage.head()
```

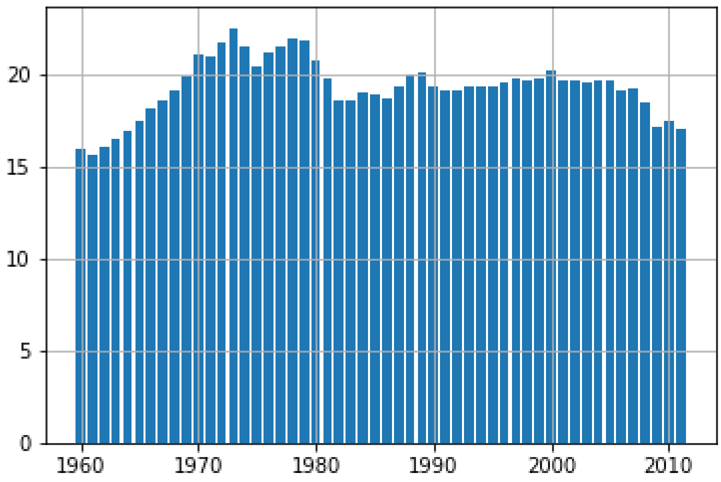
Out[11]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
22232	United States	USA	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1960	15.999779
48708	United States	USA	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1961	15.681256
77087	United States	USA	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1962	16.013937
105704	United States	USA	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1963	16.482762
134742	United States	USA	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1964	16.968119

Let's see how emissions have changed over time using MatplotLib

In [12]:

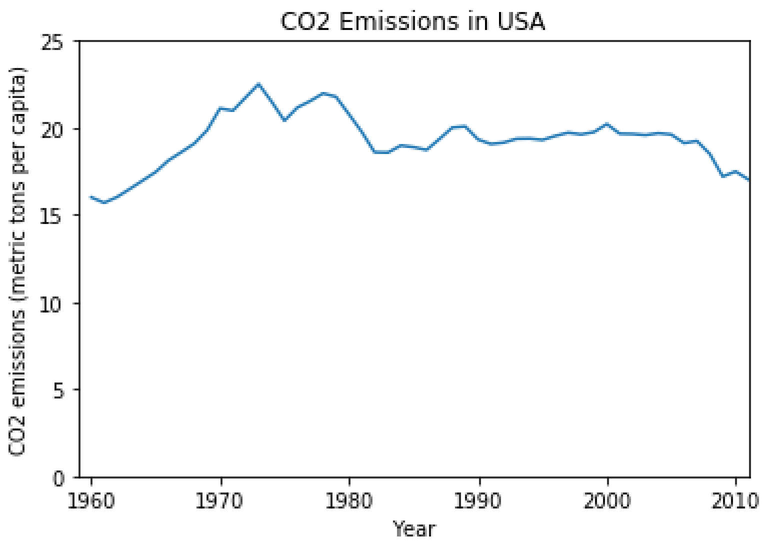
```
# get the years
years = stage['Year'].values

# get the values
co2 = stage['Value'].values

#create
plt.bar(years, co2)
plt.grid(True)
plt.show()
```



Turns out emissions per capita have dropped a bit over time, but let's make this graphic a bit more appealing before we continue to explore it.

In [13]:

```
# switch to a line plot
plt.plot(stage['Year'].values, stage['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel(stage['IndicatorName'].iloc[0])

# Label the figure
plt.title('CO2 Emissions in USA')

# to make more honest, start the y axis at 0, 如果不加上的話, y只從最低的15開始
plt.axis([1959, 2011, 0 , 25]) #前兩個值為x區間, 後兩個值為y區間

plt.show()
```



Using Histograms to explore the distribution of values

We could also visualize this data as a histogram to better explore the ranges of values in CO2 production per year.

In [14]:

```
# If you want to just include those within one standard deviation for the mean, you
# lower = stage['Value'].mean() - stage['Value'].std()
# upper = stage['Value'].mean() + stage['Value'].std()
# hist_data = [x for x in stage[:10000]['Value'] if x>lower and x<upper ]

# Otherwise, let's look at all the data
hist_data = stage['Value'].values
hist_data
```

Out[14]:

```
array([15.99977916, 15.68125552, 16.0139375 , 16.48276215, 16.9681185
8,
       17.45172525, 18.12107301, 18.59831788, 19.08938916, 19.8579456
6,
       21.11125227, 20.98020348, 21.74864198, 22.51058213, 21.5029303
8,
       20.40222407, 21.15761537, 21.53248401, 21.97300469, 21.7804369
8,
       20.78648774, 19.76676417, 18.59049523, 18.57154371, 18.9767502
7,
       18.88231274, 18.72072272, 19.35033442, 20.01041341, 20.0757697
8,
       19.32336817, 19.06223666, 19.14555576, 19.36346258, 19.3765564
4,
       19.29565986, 19.52789051, 19.71427574, 19.6151546 , 19.7478147
8,
       20.20761476, 19.65619321, 19.63919577, 19.57623905, 19.6835813
5,
       19.61027504, 19.11613882, 19.23746045, 18.48923375, 17.1923791
,
       17.48479218, 17.02021634])
```

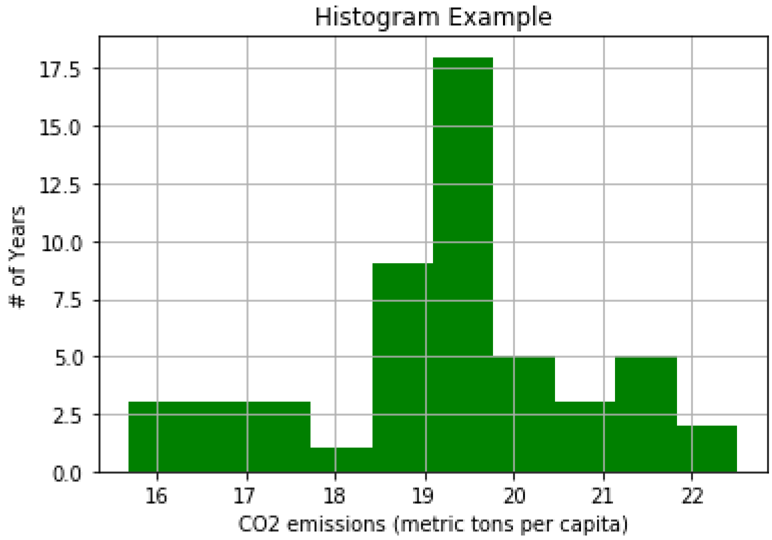
In [15]:

```
print(len(hist_data))
```

```
52
```

In [16]:

```
# the histogram of the data
plt.hist(hist_data, color = 'green')

plt.xlabel(stage['IndicatorName'].iloc[0])
plt.ylabel('# of Years')
plt.title('Histogram Example')

plt.grid(True) #畫方格

plt.show()
```



what we get is a histogram of CO2 emissions per capita for the US.
So the USA has many years where it produced CO2 between 19-20 metric tons per capita with outliers on either side.

But how do the USA's numbers relate to those of other countries?

In [17]:

```
# select CO2 emissions for all countries in 2011
hist_indicator = 'CO2 emissions \(metric'
hist_year = 2011

mask1 = data['IndicatorName'].str.contains(hist_indicator)
mask2 = data['Year'].isin([hist_year]) #.isin() 選擇只有2011年份

# apply our mask
co2_2011 = data[mask1 & mask2]
co2_2011.head() #按照國家順序名稱排列
```

Out[17]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
5026275	Arab World	ARB	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	4.724500
5026788	Caribbean small states	CSS	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	9.692960
5027295	Central Europe and the Baltics	CEB	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	6.911131
5027870	East Asia & Pacific (all income levels)	EAS	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	5.859548
5028456	East Asia & Pacific (developing only)	EAP	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	5.302499

我們可以猜想U S的CO2 emission per capita一定比這幾項來得高

For how many countries do we have CO2 per capita emissions data in 2011

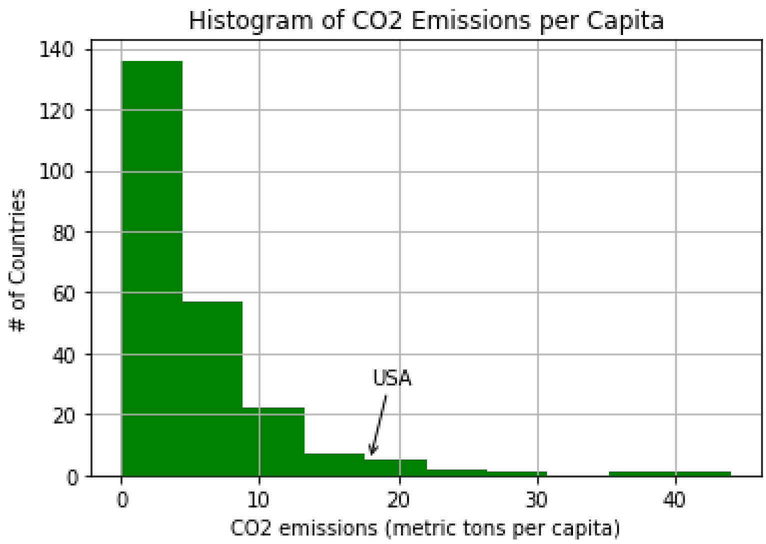
In [18]:

```
print(len(co2_2011)) #共232國家, 包含美國
```

```
232
```

In [19]:

```
# let's plot a histogram of the emmissions per capita by country

# subplots returns a touple with the figure, axis attributes.

fig, ax = plt.subplots()

ax.annotate('USA',
            xy = (18, 5), xycoords = 'data',
            xytext = (18, 30), textcoords = 'data',
            arrowprops = dict(arrowstyle = '->',
                              connectionstyle = 'arc3'),
            )

plt.hist(co2_2011['Value'], color = 'green')

plt.xlabel(stage['IndicatorName'].iloc[0])
plt.ylabel('# of Countries')
plt.title('Histogram of CO2 Emissions per Capita')

#plt.axis([10, 22, 0, 14])

plt.grid(True)

plt.show()
```



[https://matplotlib.org/users/annotations_guide.html (https://matplotlib.org/users/annotations_guide.html)](https://matplotlib.org/users/annotations_guide.html) 可參考annotating 用法

Most of countries have CO2 emissions in the range of 0 to 10 metric tons per capita.
The US, at around 17 in 2011, is actually a real outlier.
So the USA, at ~18 CO2 emissions (metric tons per capital) is quite high among all countries.

An interesting next step, which we'll save for you, would be to explore how this relates to other industrialized nations and to look at the outliers with those values in the 40s!

In [20]:

```
# 總共有幾筆數值在2011年
value = co2_2011['Value'].unique().tolist()
len(value)
```

Out[20]:

```
232
```

In [21]:

```
# value 區間
print(min(value), 'to ', max(value))
```

```
0.0213499260634489 to  44.0189263670224
```

In [22]:

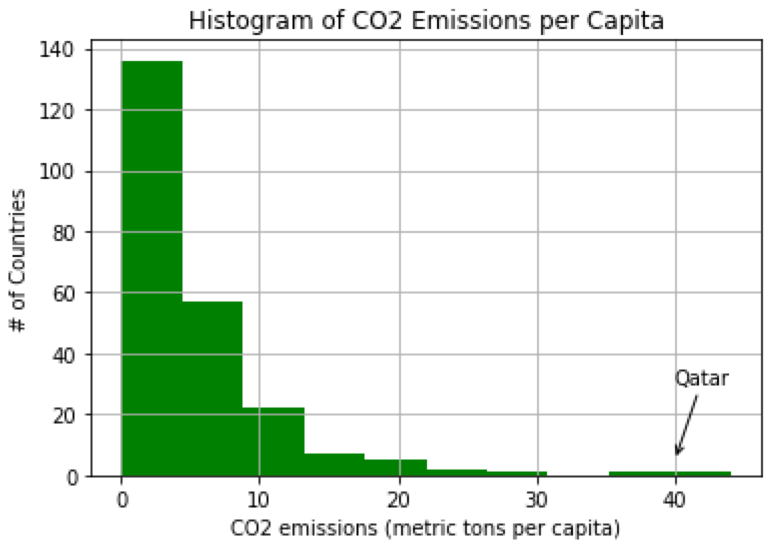
```
#用DataFrame.sort_values排序由大到小，可以查出最多CO2排放量國家在Qatar
#參閱sort_values用法: https://pandas.pydata.org/pandas-docs/stable/generated/pandas.D
df = pd.DataFrame(co2_2011).sort_values(by = ['Value'], ascending = False)
df.head()
```

Out[22]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
5161482	Qatar	QAT	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	44.018926
5188137	Trinidad and Tobago	TTO	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	37.140054
5122885	Kuwait	KWT	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	28.102662
5067585	Brunei Darussalam	BRN	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	24.392013
5053556	Aruba	ABW	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	23.922412

In [23]:

```
# let's plot a histogram of the emmissions per capita by country

# subplots returns a touple with the figure, axis attributes.

fig, ax = plt.subplots()

ax.annotate('Qatar',
            xy = (40, 5), xycoords = 'data',
            xytext = (40, 30), textcoords = 'data',
            arrowprops = dict(arrowstyle = '->',
                              connectionstyle = 'arc3'),
            )

plt.hist(co2_2011['Value'], color = 'green')

plt.xlabel(stage['IndicatorName'].iloc[0])
plt.ylabel('# of Countries')
plt.title('Histogram of CO2 Emissions per Capita')

#plt.axis([10, 22, 0, 14])

plt.grid(True)

plt.show()
```



Matplotlib: Basic Plotting, Part 2

Relationship between GDP and CO2 Emissions in USA

In [24]:

```
# select GDP Per capita emissions for the United States
hist_indicator = 'GDP per capita \(constant 2005' #僅看 constant 2005 US$
hist_country = 'USA'

mask1 = data['IndicatorName'].str.contains(hist_indicator)
mask2 = data['CountryCode'].str.contains(hist_country)

# stage is just those indicators matching the USA for country code and CO2 emissions
gdp_stage = data[mask1 & mask2]

#plot gdp_stage vs stage
```

In [25]:

```
gdp_stage.head(2)
```

Out[25]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
22282	United States	USA	GDP per capita (constant 2005 US$)	NY.GDP.PCAP.KD	1960	15482.707760
48759	United States	USA	GDP per capita (constant 2005 US$)	NY.GDP.PCAP.KD	1961	15578.409657

In [26]:

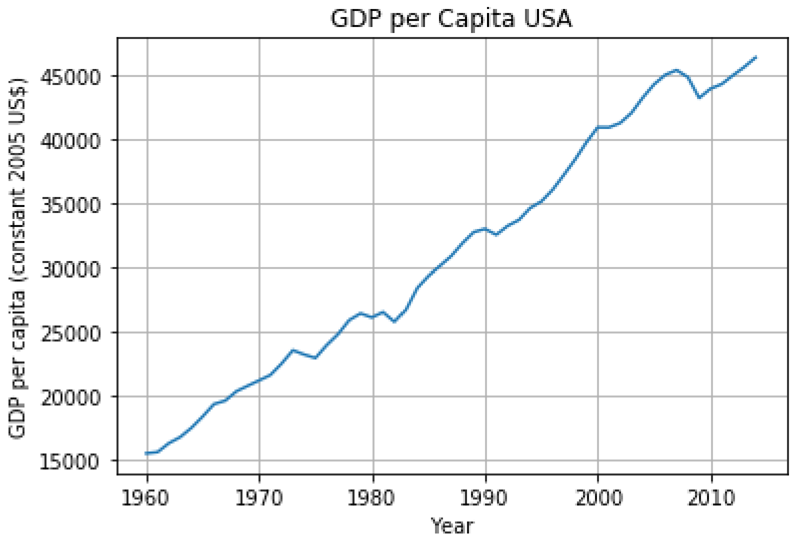
```
stage.head(2)
```

Out[26]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
22232	United States	USA	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1960	15.999779
48708	United States	USA	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	1961	15.681256

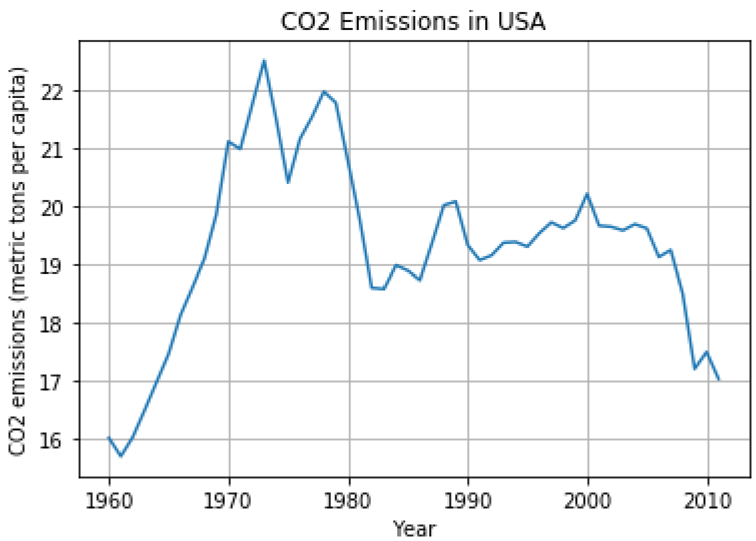
In [27]:

```
#觀察 GDP per Capita vs Year的變化
# switch to the line plot
plt.plot(gdp_stage['Year'].values, gdp_stage['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel(gdp_stage['IndicatorName'].iloc[0])

# Label the figure
plt.title('GDP per Capita USA')


plt.grid(True)

plt.show()
```



In [28]:

```
# 再次作圖觀察 CO2 emissions per Capita vs Year的變化
# switch to a line plot
plt.plot(stage['Year'].values, stage['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel(stage['IndicatorName'].iloc[0])

# Label the figure
plt.title('CO2 Emissions in USA')

# to make more honest, start the y axis at 0, 如果不加上的話, y只從最低的15開始
#plt.axis([1959, 2011, 0 , 25]) #前兩個值為x區間, 後兩個值為y區間

plt.grid(True)
plt.show()
```



So although we've seen a decline in the CO2 emissions per capita, it does not seem to translate to a decline in GDP per capita.
即便減少了CO2排放量, GDP沒有跟著減少

ScatterPlot for comparing GDP against CO2 emissions (per capita)

First, we'll need to make sure we're looking at the same time frames

In [29]:

```
print('GDP min Year :', gdp_stage['Year'].min() ,'Max :', gdp_stage["Year"].max())
print('CO2 min Year :', stage['Year'].min(), 'Max :', stage['Year'].max())
```

```
GDP min Year : 1960 Max : 2014
CO2 min Year : 1960 Max : 2011
```

觀察到GDP跟CO2排放量最少跟最低的年份在1960, 但最CO2排放量大值的年份跟GDP最高年份不同.
做這點確認很重要, 如果是一樣, 或許我們不需要做scatter plot, 但如果不同， 有必要做scatter plot

We have 3 extra years of GDP data, so let's **trim those off** so the scatterplot has equal length arrays to compare (this is actually required by scatterplot)

In [30]:

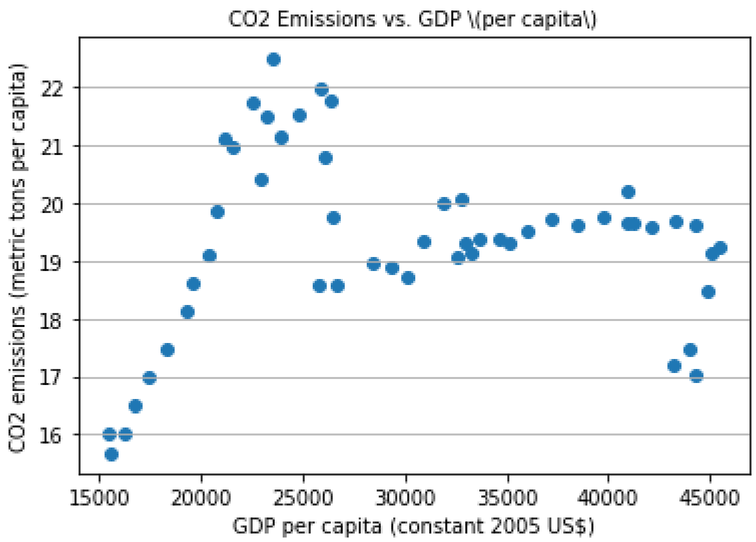
```
# To do the trimming, let's ask for the years before 2012
gdp_stage_trunc = gdp_stage[gdp_stage['Year'] < 2012]

#Check that the data has the same number for both GDP and the CO2 emissions
print(len(gdp_stage_trunc))
print(len(stage))
```

```
52
52
```

結論得到我們都有52 years 的data在所選的區域內

In [31]:

```
%matplotlib inline
import matplotlib.pyplot as plt

fig, axis = plt.subplots()
# Grid Lines, Xticks, XLabel, YLabel

# label x, y, and title
axis.set_xlabel(gdp_stage_trunc['IndicatorName'].iloc[0], fontsize = 10)
axis.set_ylabel(stage['IndicatorName'].iloc[0], fontsize = 10)
axis.set_title ('CO2 Emissions vs. GDP \(per capita\)', fontsize = 10)

# grid open only for y-axis
axis.yaxis.grid(True)

X = gdp_stage_trunc['Value']
Y = stage['Value']

axis.scatter(X, Y)
plt.show()
```



This doesn't look like a strong relationship. We can test this by looking at correlation.

In [32]:

```
# NP裡頭的 correlation coefficient function查看兩者關係
np.corrcoef(gdp_stage_trunc['Value'], stage['Value'])
```

Out[32]:

```
array([[1.        , 0.07676005],
       [0.07676005, 1.        ]])
```

A correlation of 0.07 is pretty weak, but you'll learn more about correlation in the next course.

You could continue to explore this to see if other countries have a closer relationship between CO2 emissions and GDP. Perhaps it is stronger for developing countries?

Want more ?

Matplotlib Examples Library

http://matplotlib.org/examples/index.html (http://matplotlib.org/examples/index.html)

Using Folium Library for Geographic Overlays

Further exploring CO2 Emissions per capita in the World Development Indicators Dataset

In [33]:

```
import folium
import pandas as pd
```

Country coordinates for plotting

source: https://github.com/python-visualization/folium/blob/master/examples/data/world-countries.json (https://github.com/python-visualization/folium/blob/master/examples/data/world-countries.json)

In [34]:

```
country_geo = 'world-countries.json'
```

In [35]:

```
# Read on the World Development Indicators Database
data = pd.read_csv('world-development-indicators/Indicators.csv')
data.shape
```

Out[35]:

```
(5656458, 6)
```

In [36]:

```
data.head()
```

Out[36]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
0	Arab World	ARB	Adolescent fertility rate (births per 1,000 wo...	SP.ADO.TFRT	1960	1.335609e+02
1	Arab World	ARB	Age dependency ratio (% of working-age populat...	SP.POP.DPND	1960	8.779760e+01
2	Arab World	ARB	Age dependency ratio, old (% of working-age po...	SP.POP.DPND.OL	1960	6.634579e+00
3	Arab World	ARB	Age dependency ratio, young (% of working-age ...	SP.POP.DPND.YG	1960	8.102333e+01
4	Arab World	ARB	Arms exports (SIPRI trend indicator values)	MS.MIL.XPRT.KD	1960	3.000000e+06

Pull out CO2 emisions for every country in 2011

In [37]:

```
# select CO2 emissions for all countries in 2011
hist_indicator = 'CO2 emissions \(metric'
hist_year = 2011

mask1 = data['IndicatorName'].str.contains(hist_indicator)
mask2 = data['Year'].isin([hist_year])

# apply our mask
stage = data[mask1 & mask2]
stage.head()
```

Out[37]:

	CountryName	CountryCode	IndicatorName	IndicatorCode	Year	Value
5026275	Arab World	ARB	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	4.724500
5026788	Caribbean small states	CSS	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	9.692960
5027295	Central Europe and the Baltics	CEB	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	6.911131
5027870	East Asia & Pacific (all income levels)	EAS	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	5.859548
5028456	East Asia & Pacific (developing only)	EAP	CO2 emissions (metric tons per capita)	EN.ATM.CO2E.PC	2011	5.302499

Setup our data for plotting.

Create a data frame with just the **country codes** and the **values** we want plotted.

In [38]:

```
plot_data = stage[['CountryCode', 'Value']]
plot_data.head()
```

Out[38]:

	CountryCode	Value
5026275	ARB	4.724500
5026788	CSS	9.692960
5027295	CEB	6.911131
5027870	EAS	5.859548
5028456	EAP	5.302499

In [39]:

```
# Label for the Legend
hist_indicator = stage.iloc[0]['IndicatorName']
```

Visualize CO2 emissions per capita using Folium

Folium provides interactive maps with the ability to create sophisticated overlays for data visualization

In [40]:

```
# Setup a folium map at a high-level zoom
map = folium.Map(location= [100, 0], zoom_start = 1.5)
```

In [41]:

```
# choropleth maps bind Pandas Data Frames and json geometries.  This allows us to qu

map.choropleth(geo_data= country_geo, data=plot_data,
               columns=['CountryCode', 'Value'],
               key_on='feature.id',
               fill_color='YlGnBu', fill_opacity=0.7, line_opacity=0.2,
               legend_name=hist_indicator)
```

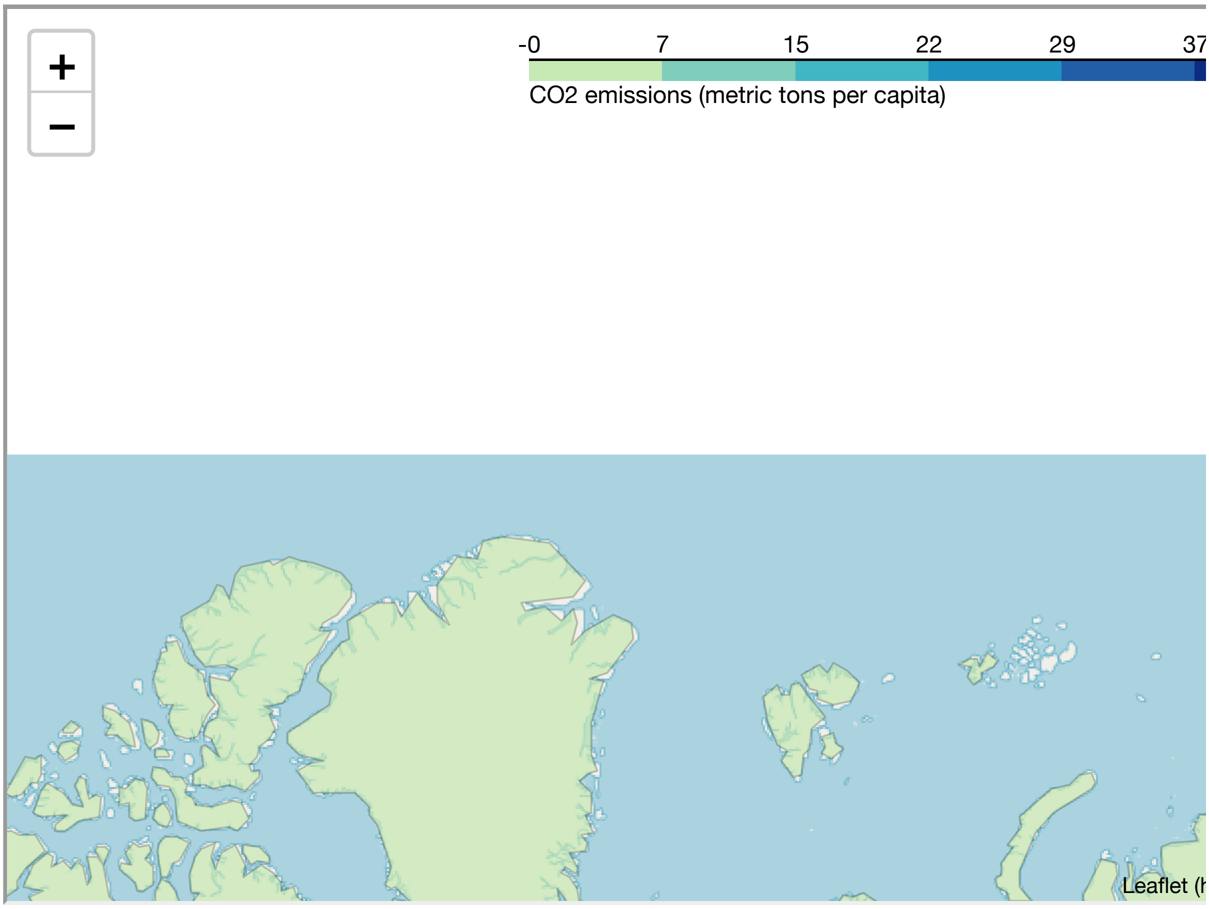
In [42]:

```
# Create Folium plot
map.save('plot_data.html')
```

In [43]:

```
# Import the Folium interactive html file
from IPython.display import HTML
HTML('<iframe src=plot_data.html width=700 height=450></iframe>')
```

Out[43]:



More Folium Examples can be found at: [http://python-visualization.github.io/folium/quickstart.html#Getting-Started (http://python-visualization.github.io/folium/quickstart.html#Getting-Started)](http://python-visualization.github.io/folium/quickstart.html#Getting-Started)

Documentation at: [http://python-visualization.github.io/folium/ (http://python-visualization.github.io/folium/)](http://python-visualization.github.io/folium/)