In [1]:

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

Steps

1. Reading and Characterizing the Data `(ACQUIRE)`
2. Exploration `(PREPARE)`
3. Cleaning and Filtering the Data for our requirements `(PREPARE)`
4. Analysis `(ANALYZE)`
5. Results `(REPORT)`

I. Characterizing the data (ACQUIRE)

Code below is to `read` the data file.

In [2]:

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

Code below is to see the `number` of `rows` and `columns` in the data.

In [3]:

```
data.shape
```

Out[3]:

```
(5656458, 6)
```

Code below is to see a `sample` of the data.

In [4]:
```
data.head()
#data.tail()
```

Out[4]:

	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

Before we start exploring the data, we want a clearer picture of the data. Hence we ask a few questions.

Q1. How many unique indicators do we have?

Code below is to find out the `length` of the indicators.

In [5]:
```
indicators = data['IndicatorName'].unique().tolist()
len(indicators)
```

Out[5]: 1344

Q2. How many years of data do we have ?

Code below is to find out `number` of years.

In [6]:
```
# How many years of data do we have ?
years = data['Year'].unique().tolist()
len(years)
#years
```

Out[6]: 56

Q3. What is the range of years?

Code below is to find out the `range` of years.

In [7]:
```
print(min(years)," to ",max(years))
```

```
1960  to  2015
```

Now we have understood the `basic characteristics` of the data.

II. Exploration (PREPARE)

Code below is to display all the indicators in order to explore the indicators, and to figure out what are the best metrics to measure the `effects of quality of air on the quality of life` .

In [8]:
```
indicators
```

Out[8]:
```
['Adolescent fertility rate (births per 1,000 women ages 15-19)',
 'Age dependency ratio (% of working-age population)',
 'Age dependency ratio, old (% of working-age population)',
 'Age dependency ratio, young (% of working-age population)',
 'Arms exports (SIPRI trend indicator values)',
 'Arms imports (SIPRI trend indicator values)',
 'Birth rate, crude (per 1,000 people)',
 'CO2 emissions (kt)',
 'CO2 emissions (metric tons per capita)',
 'CO2 emissions from gaseous fuel consumption (% of total)',
 'CO2 emissions from liquid fuel consumption (% of total)',
 'CO2 emissions from liquid fuel consumption (kt)',
 'CO2 emissions from solid fuel consumption (% of total)',
 'Death rate, crude (per 1,000 people)',
 'Fertility rate, total (births per woman)',
 'Fixed telephone subscriptions',
 'Fixed telephone subscriptions (per 100 people)',
 'Hospital beds (per 1,000 people)',
 'International migrant stock (% of population)',
```

Air Quality Indicators chosen are:

1. PM2.5 air pollution, mean annual exposure (micrograms per cubic meter)
2. PM2.5 air pollution, population exposed to levels exceeding WHO guideline value (% of total)
3. CO2 emissions (kt)
4. CO2 emissions (metric tons per capita)
5. Nitrous oxide emissions (thousand metric tons of CO2 equivalent)
6. Methane emissions (kt of CO2 equivalent)
7. SF6 gas emissions (thousand metric tons of CO2 equivalent)
8. HFC gas emissions (thousand metric tons of CO2 equivalent)
9. PFC gas emissions (thousand metric tons of CO2 equivalent)
10. Other greenhouse gas emissions, HFC, PFC and SF6 (thousand metric tons of CO2 equivalent)

Health Indicators chosen are:

1. Birth rate, crude (per 1,000 people)
2. Mortality rate, infant (per 1,000 live births)
3. Fertility rate, total (births per woman)
4. Life expectancy at birth, total (years)
5. Population growth (annual %)
6. Prevalence of stunting, height for age (% of children under 5)
7. Low-birthweight babies (% of births)

III. Cleaning and Filtering the Data for our requirements (PREPARE)

Code below is to `create a mask` for `air quality indicators` .

In [9]:

```
indicator1 = 'PM2.5 air pollution, mean annual exposure \(micrograms'
indicator2 = 'PM2.5 air pollution, population exposed to '
indicator3 = 'CO2 emissions \(kt'
indicator4 = 'CO2 emissions \(metric'
indicator5 = 'Nitrous oxide emissions \(thousand'
indicator6 = 'Methane emissions \(kt of CO2'
indicator7 = 'SF6 gas emissions \(thousand'
indicator8 = 'HFC gas emissions \(thousand'
indicator9 = 'PFC gas emissions \(thousand'
indicator10 = 'Other greenhouse gas emissions, HFC'

mask1 = data['IndicatorName'].str.contains(indicator1)
mask2 = data['IndicatorName'].str.contains(indicator2)
mask3 = data['IndicatorName'].str.contains(indicator3)
mask4 = data['IndicatorName'].str.contains(indicator4)
mask5 = data['IndicatorName'].str.contains(indicator5)
mask6 = data['IndicatorName'].str.contains(indicator6)
mask7 = data['IndicatorName'].str.contains(indicator7)
mask8 = data['IndicatorName'].str.contains(indicator8)
mask9 = data['IndicatorName'].str.contains(indicator9)
mask10 = data['IndicatorName'].str.contains(indicator10)
```

Code below is to `create a mask for health indicators`.

In [10]:

```
h_indicator1 = 'Birth rate, crude \('
h_indicator2 = 'Mortality rate, infant \(per'
h_indicator3 = 'Fertility rate, total \('
h_indicator4 = 'Life expectancy at birth, t'
h_indicator5 = 'Population growth \(a'
h_indicator6 = 'Prevalence of stunting, height for age \('
h_indicator7 = 'Low-birthweight babies \('

h_mask1 = data['IndicatorName'].str.contains(h_indicator1)
h_mask2 = data['IndicatorName'].str.contains(h_indicator2)
h_mask3 = data['IndicatorName'].str.contains(h_indicator3)
h_mask4 = data['IndicatorName'].str.contains(h_indicator4)
h_mask5 = data['IndicatorName'].str.contains(h_indicator5)
h_mask6 = data['IndicatorName'].str.contains(h_indicator6)
h_mask7 = data['IndicatorName'].str.contains(h_indicator7)
```

Code below is to `create a mask` to filter out data for a `specific country.` For the analysis, I have chosen `The USA` .

In [11]:
```
country = 'USA'
country_mask = data['CountryCode'].str.contains(country)
```

Code below is to `create individual dataframes` for the `chosen indicators` for both `air quality` and `health` for a specific country.

In [12]:
```
df1 = data[mask1 & country_mask].copy()
df2 = data[mask2 & country_mask].copy()
df3 = data[mask3 & country_mask].copy()
df4 = data[mask4 & country_mask].copy()
df5 = data[mask5 & country_mask].copy()
df6 = data[mask6 & country_mask].copy()
df7 = data[mask7 & country_mask].copy()
df8 = data[mask8 & country_mask].copy()
df9 = data[mask9 & country_mask].copy()
df10 = data[mask10 & country_mask].copy()

hdf1 = data[h_mask1 & country_mask].copy()
hdf2 = data[h_mask2 & country_mask].copy()
hdf3 = data[h_mask3 & country_mask].copy()
hdf4 = data[h_mask4 & country_mask].copy()
hdf5 = data[h_mask5 & country_mask].copy()
hdf6 = data[h_mask6 & country_mask].copy()
hdf7 = data[h_mask7 & country_mask].copy()
```

Now we want to `delete` : `1. Columns not required for analysis` , `2. Rows containing Nil value` , and then `reindex` the rows for `lighter operation` and `quicker runtimes`

Code below is to execute the 3 operations mentioned above.

In [13]:

```
df1.drop(df1.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df1.dropna(subset=['Value'])
df1.reset_index(drop = True, inplace=True)

df2.drop(df2.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df2.dropna(subset=['Value'])
df2.reset_index(drop = True, inplace=True)

df3.drop(df3.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df3.dropna(subset=['Value'])
df3.reset_index(drop = True, inplace=True)

df4.drop(df4.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df4.dropna(subset=['Value'])
df4.reset_index(drop = True, inplace=True)

df5.drop(df5.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df5.dropna(subset=['Value'])
df5.reset_index(drop = True, inplace=True)

df6.drop(df6.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df6.dropna(subset=['Value'])
df6.reset_index(drop = True, inplace=True)

df7.drop(df7.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df7.dropna(subset=['Value'])
df7.reset_index(drop = True, inplace=True)

df8.drop(df8.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df8.dropna(subset=['Value'])
df8.reset_index(drop = True, inplace=True)

df9.drop(df9.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df9.dropna(subset=['Value'])
df9.reset_index(drop = True, inplace=True)

df10.drop(df10.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
df10.dropna(subset=['Value'])
df10.reset_index(drop = True, inplace=True)
```

```
hdf1.drop(hdf1.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
hdf1.dropna(subset=['Value'])
hdf1.reset_index(drop = True, inplace=True)

hdf2.drop(hdf2.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
hdf2.dropna(subset=['Value'])
hdf2.reset_index(drop = True, inplace=True)

hdf3.drop(hdf3.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
hdf3.dropna(subset=['Value'])
hdf3.reset_index(drop = True, inplace=True)

hdf4.drop(hdf4.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
hdf4.dropna(subset=['Value'])
hdf4.reset_index(drop = True, inplace=True)

hdf5.drop(hdf5.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
hdf5.dropna(subset=['Value'])
hdf5.reset_index(drop = True, inplace=True)

hdf6.drop(hdf6.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
hdf6.dropna(subset=['Value'])
hdf6.reset_index(drop = True, inplace=True)

hdf7.drop(hdf7.columns[[0, 1, 2, 3]], axis = 1, inplace = True)
hdf7.dropna(subset=['Value'])
hdf7.reset_index(drop = True, inplace=True)
```

Code below is to `individually` check if the above operation worked.

In [14]:

```
#add/remove

#d10
hdf7
```

Out[14]:

	Year	Value
0	2002	8.0
1	2010	8.1

IV. Analysis (ANALYZE)

Code below is to individually examine examine the final dataframes we will use to perform the analysis. We want to check if we have the required data for 54 years.

`df` Range : `df1` to `df10`

`hdf` Range : `hdf1` to `hdf7`

In [15]:

```
#Change the dataframe number according to the range

#df10
#hdf7

#df10.shape
hdf7.shape
```

Out[15]: (2, 2)

Post examination of the dataframes individually, We have found that:

No of years of data available for:

- df1 : 7
- df2 : 7
- df3 : 52

- df4 : 52
- df5 : 5
- df6 : 5
- df7 : 5
- df8 : 5
- df9 : 5
- df10 : 5

- hdf1 : 54
- hdf2 : 56
- hdf3 : 54
- hdf4 : 54
- hdf5 : 55
- hdf6 : 7
- hdf7 : 2

Conclusion

1. We `do not` have sufficient data for any `air quality` indicators `except` for `CO2 emissions`.
2. We `do not` have sufficient data for `health indicators` for `prevalance of stunting` and `low-birth weight babies`.

Due to data constraints, We have chosen `CO2 Emissions(kt)` as the only indicator for `air quality`,

And we have chosen the following `5 indicators` for health `quality`.

1. `Birth rate, crude (per 1,000 people)`
2. `Mortality rate, infant (per 1,000 live births)`
3. `Fertility rate, total (births per woman)`
4. `Life expectancy at birth, total (years)`
5. `Population growth (annual %)`

The analysis that will be performed is the `Effect of CO2 emissions(kt)` on

1. `Birth rate, crude (per 1,000 people)`
2. `Mortality rate, infant (per 1,000 live births)`
3. `Fertility rate, total (births per woman)`
4. `Life expectancy at birth, total (years)`

5. `Population growth (annual %)`

Code below is to check if the data present have the `same timeline`.

In [16]:
```
print("CO2 Emissions Min Year = ", df3['Year'].min(), " Max: ", df3['Year'].max())
print("Birth Rate Min Year = ", hdf1['Year'].min(), " Max: ", hdf1['Year'].max())
print("Mortality Rate Min Year = ", hdf2['Year'].min(), " Max: ", hdf2['Year'].max())
print("Fertility Min Year = ", hdf3['Year'].min(), " Max: ", hdf3['Year'].max())
print("Life Expectancy at birth, total Min Year = ", hdf4['Year'].min(), " Max: ", hdf4['Year'].max())
print("Population Growth Min Year = ", hdf5['Year'].min(), " Max: ", hdf5['Year'].max())
```

```
CO2 Emissions Min Year =  1960  Max:  2011
Birth Rate Min Year =  1960  Max:  2013
Mortality Rate Min Year =  1960  Max:  2015
Fertility Min Year =  1960  Max:  2013
Life Expectancy at birth, total Min Year =  1960  Max:  2013
Population Growth Min Year =  1960  Max:  2014
```

Since the `min year in common` is the `same` for all indicators and the `max year in common` for all indicators is `2011`, we will filter the data and and get data from `1960 till 2011`.

Code below is to filter the data from `1960 till 2011`.

In [17]:
```
df3 = df3[df3['Year'] < 2012]

hdf1 = hdf1[hdf1['Year'] < 2012]
hdf2 = hdf2[hdf2['Year'] < 2012]
hdf3 = hdf3[hdf3['Year'] < 2012]
hdf4 = hdf4[hdf4['Year'] < 2012]
hdf5 = hdf5[hdf5['Year'] < 2012]
```

Code below is to check if our filter for the `Years` column worked.

In [18]:

```
print("CO2 Emissions Min Year = ", df3['Year'].min(), " Max: ", df3['Year'].max())
print("Birth Rate Min Year = ", hdf1['Year'].min(), " Max: ", hdf1['Year'].max())
print("Mortality Rate Min Year = ", hdf2['Year'].min(), " Max: ", hdf2['Year'].max())
print("Fertility Min Year = ", hdf3['Year'].min(), " Max: ", hdf3['Year'].max())
print("Life Expectancy at birth, total Min Year = ", hdf4['Year'].min(), " Max: ", hdf4['Year'].max())
print("Population Growth Min Year = ", hdf5['Year'].min(), " Max: ", hdf5['Year'].max())
```

```
CO2 Emissions Min Year =  1960  Max:  2011
Birth Rate Min Year =  1960  Max:  2011
Mortality Rate Min Year =  1960  Max:  2011
Fertility Min Year =  1960  Max:  2011
Life Expectancy at birth, total Min Year =  1960  Max:  2011
Population Growth Min Year =  1960  Max:  2011
```

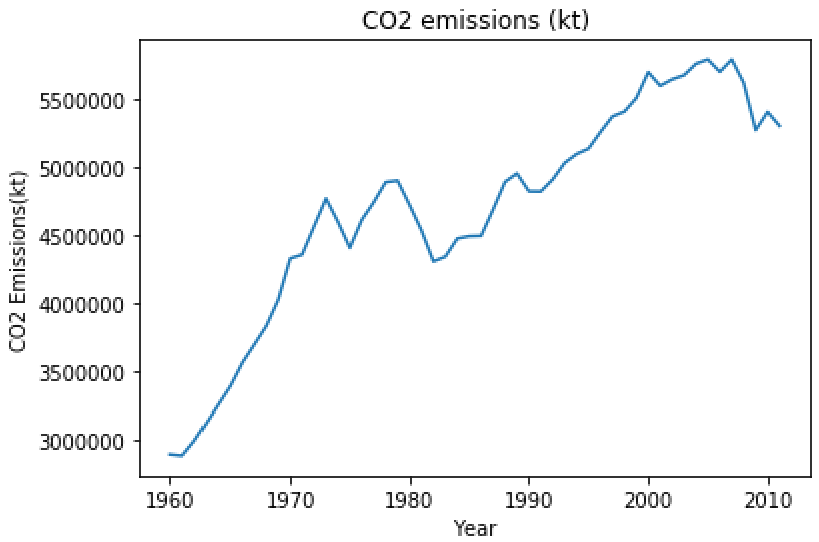
We can observe that the filter has worked and now, `all` the `indicators` have the `same timeline` .

We want to `explore` the values for `air quality` first.

Code below is to see the trend for `CO2 Emissions(kt)` over the years through a line plot.

In [19]:

```
# switch to a line plot
plt.plot(df3['Year'].values, df3['Value'].values)

# Label the axes
plt.xlabel('Year')
plt.ylabel('CO2 Emissions(kt)')
axis.set_xlabel(x ,fontsize=12)
axis.set_ylabel(y ,fontsize=12)

#label the figure
plt.title('CO2 emissions (kt)', fontsize=15)

plt.show()
plt.savefig('CO2 Emissions(kt).png', bbox_inches='tight')
```




```
<Figure size 432x288 with 0 Axes>
```

We can observe that the `general trend` for `CO2 emissions` is `increasing` , but has shown `degrowth` towards the `end` .

We want to `explore` the values for `all` the `indicators` that represent `quality of life` first.

Code below is to `create a single dataframe` with the `values` of the `health indicators` for `lighter operation` and `quicker runtimes` .

In [20]:
```
correl_hdfs = pd.concat([hdf1, hdf2, hdf3, hdf4, hdf5], axis=1, join='inner')
correl_hdfs.drop(correl_hdfs.columns[[2, 4, 6, 8]], axis = 1, inplace = True)
correl_hdfs.columns = ['hdf1', 'hdf2', 'hdf3', 'hdf4', 'hdf5']
```

Code below is to check if the above operation worked.

In [21]:

```
correl_hdfs
```

Out[21]:

	hdf1	hdf2	hdf3	hdf4	hdf5
0	23.7	25.9	3.6540	69.770732	1.701993
1	23.3	25.4	3.6200	70.270732	1.657730
2	22.4	24.9	3.4610	70.119512	1.537997
3	21.7	24.4	3.3190	69.917073	1.439165
4	21.1	23.8	3.1900	70.165854	1.389046
5	19.4	23.3	2.9130	70.214634	1.250172
6	18.4	22.7	2.7210	70.212195	1.154893
7	17.8	22.0	2.5580	70.560976	1.088881
8	17.6	21.3	2.4640	69.951220	0.998461
9	17.9	20.6	2.4560	70.507317	0.977243
10	18.4	19.9	2.4800	70.807317	1.165003
11	17.2	19.1	2.2660	71.107317	1.264334
12	15.6	18.3	2.0100	71.156098	1.070523
13	14.8	17.5	1.8790	71.356098	0.954477
14	14.8	16.7	1.8350	71.956098	0.913660
15	14.6	16.0	1.7740	72.604878	0.985986
16	14.6	15.2	1.7380	72.856098	0.950220
17	15.1	14.5	1.7900	73.256098	1.005772
18	15.0	13.8	1.7600	73.356098	1.059573
19	15.6	13.2	1.8080	73.804878	1.103577
20	15.9	12.6	1.8395	73.658537	0.959590
21	15.8	12.1	1.8120	74.007317	0.981415
22	15.9	11.7	1.8275	74.360976	0.953318
23	15.6	11.2	1.7990	74.463415	0.914379

	hdf1	hdf2	hdf3	hdf4	hdf5
24	15.6	10.9	1.8065	74.563415	0.865817
25	15.8	10.6	1.8440	74.563415	0.886129
26	15.6	10.4	1.8375	74.614634	0.924164
27	15.7	10.2	1.8720	74.765854	0.893829
28	16.0	10.0	1.9340	74.765854	0.907999
29	16.4	9.7	2.0140	75.017073	0.944406
30	16.7	9.4	2.0810	75.214634	1.129651
31	16.2	9.1	2.0625	75.365854	1.336261
32	15.8	8.8	2.0460	75.642195	1.386886
33	15.4	8.5	2.0195	75.419512	1.318680
34	15.0	8.2	2.0015	75.574390	1.226296
35	14.6	8.0	1.9780	75.621951	1.190787
36	14.4	7.7	1.9760	75.996585	1.163412
37	14.2	7.5	1.9710	76.429268	1.203960
38	14.3	7.3	1.9990	76.580488	1.165715
39	14.2	7.2	2.0075	76.582927	1.148340
40	14.4	7.1	2.0560	76.636585	1.112769
41	14.1	7.0	2.0305	76.736585	0.989741
42	14.0	6.9	2.0205	76.836585	0.927797
43	14.1	6.8	2.0475	76.987805	0.859482
44	14.0	6.9	2.0515	77.339024	0.925484
45	14.0	6.8	2.0570	77.339024	0.921713
46	14.3	6.7	2.1080	77.587805	0.964254
47	14.3	6.6	2.1200	77.839024	0.951055
48	14.0	6.5	2.0720	77.939024	0.945865
49	13.5	6.4	2.0020	78.090244	0.876651

	hdf1	hdf2	hdf3	hdf4	hdf5
50	13.0	6.3	1.9310	78.541463	0.836054
51	12.7	6.1	1.8945	78.641463	0.764678

We will now check the `correlation` between the values for the `5 health indicators` to see if we can `omit` indicators having a `high positive correlation value` with `all` the other `indicators`.

Code below is to calculate `correlation` for columns within a dataframe.

In [22]:
```
correl_hdfs.corr(method ='pearson')
```

Out[22]:

	hdf1	hdf2	hdf3	hdf4	hdf5
hdf1	1.000000	0.861943	0.909993	-0.798085	0.767149
hdf2	0.861943	1.000000	0.749158	-0.969850	0.555799
hdf3	0.909993	0.749158	1.000000	-0.612636	0.770800
hdf4	-0.798085	-0.969850	-0.612636	1.000000	-0.500489
hdf5	0.767149	0.555799	0.770800	-0.500489	1.000000

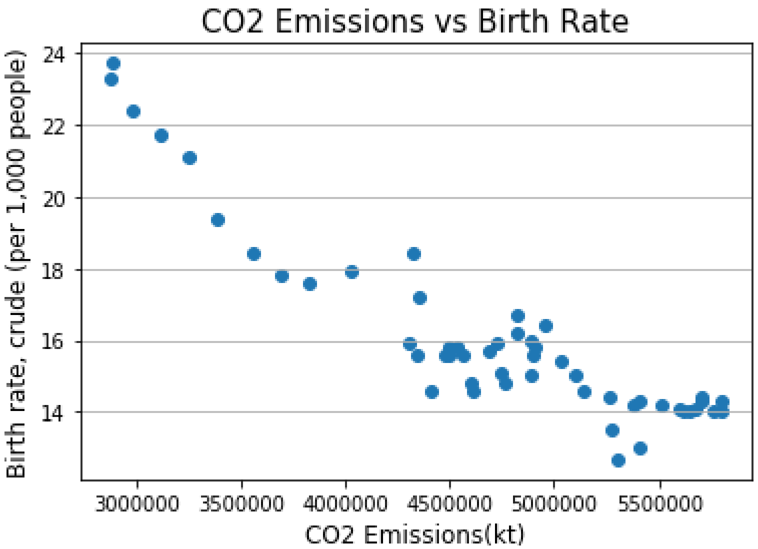
We can observe that `none` of the columns have a `significant positive correlation` with `all indicators.` Hence we will `take` into `consideration` all of the chosen indicators.

V. Results (REPORT)

1. Scatter Plot of CO2 Emissions(kt) vs Birth rate, crude (per 1,000 people)

Code below is to `create a scatter plot` and to `save` it as an `image file` to use in the presentation.

In [23]:
```
%matplotlib inline

fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

x = 'CO2 Emissions(kt)'
y = 'Birth rate, crude (per 1,000 people)'

a = 'CO2 Emissions'
b = 'Birth Rate'
axis.yaxis.grid(True)
axis.set_title(a+' vs '+b,fontsize=15)
axis.set_xlabel(x ,fontsize=12)
axis.set_ylabel(y ,fontsize=12)

X = df3['Value'].values
Y = hdf1['Value'].values

axis.scatter(X, Y)
plt.show()
plt.savefig('CO2 vs Birth Rate.png', bbox_inches='tight')

column_1 = df3["Value"]
column_2 = hdf1["Value"]
correlation = column_1.corr(column_2)

print('The correlation between '+a+' and '+b+' is: '+str(round(correlation, 3)))
```



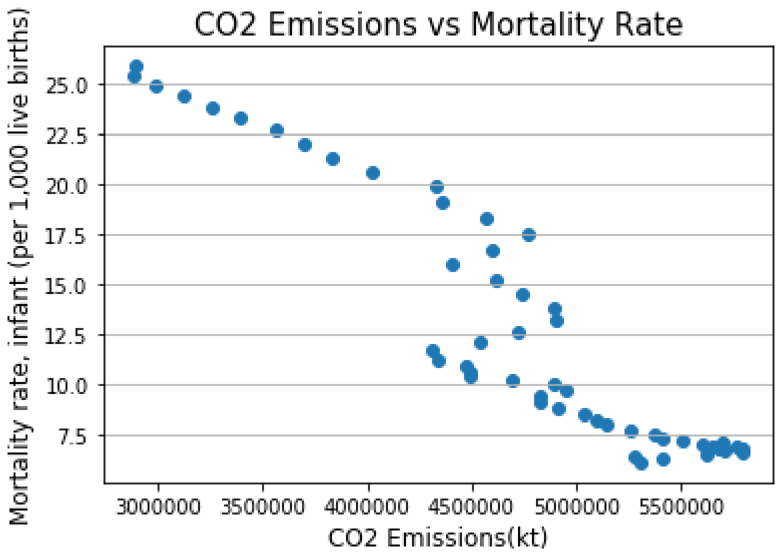

```
The correlation between CO2 Emissions and Birth Rate is: -0.91

<Figure size 432x288 with 0 Axes>
```

2. Scatter Plot of CO2 Emissions(kt) vs Mortality rate, infant (per 1,000 live births)

Code below is to `create a scatter plot` and to `save` it as an `image file` to use in the presentation.

In [24]:

```
fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

x = 'CO2 Emissions(kt)'
y = 'Mortality rate, infant (per 1,000 live births)'

a = 'CO2 Emissions'
b = 'Mortality Rate'
axis.yaxis.grid(True)
axis.set_title(a+' vs '+b,fontsize=15)
axis.set_xlabel(x ,fontsize=12)
axis.set_ylabel(y ,fontsize=12)

X = df3['Value'].values
Y = hdf2['Value'].values

axis.scatter(X, Y)
plt.show()
plt.savefig('CO2 vs Mortality Rate.png', bbox_inches='tight')

column_1 = df3["Value"]
column_2 = hdf2["Value"]
correlation = column_1.corr(column_2)

print('The correlation between '+a+' and '+b+' is: '+str(round(correlation, 3)))
```




```
The correlation between CO2 Emissions and Mortality Rate is: -0.93
```

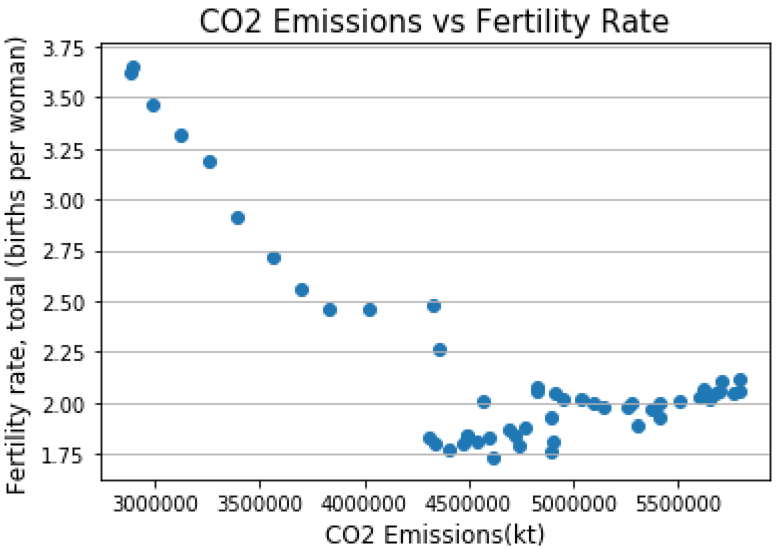
```
<Figure size 432x288 with 0 Axes>
```

3. Scatter Plot of CO2 Emissions(kt) vs Fertility rate, total (births per woman)

Code below is to `create a scatter plot` and to `save` it as an `image file` to use in the presentation.

In [25]:

```
fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

x = 'CO2 Emissions(kt)'
y = 'Fertility rate, total (births per woman)'

a = 'CO2 Emissions'
b = 'Fertility Rate'
axis.yaxis.grid(True)
axis.set_title(a+' vs '+b,fontsize=15)
axis.set_xlabel(x ,fontsize=12)
axis.set_ylabel(y ,fontsize=12)

X = df3['Value'].values
Y = hdf3['Value'].values

axis.scatter(X, Y)
plt.show()
plt.savefig('CO2 vs Fertility Rate.png', bbox_inches='tight')

column_1 = df3["Value"]
column_2 = hdf3["Value"]
correlation = column_1.corr(column_2)

print('The correlation between '+a+' and '+b+' is: '+str(round(correlation, 3)))
```



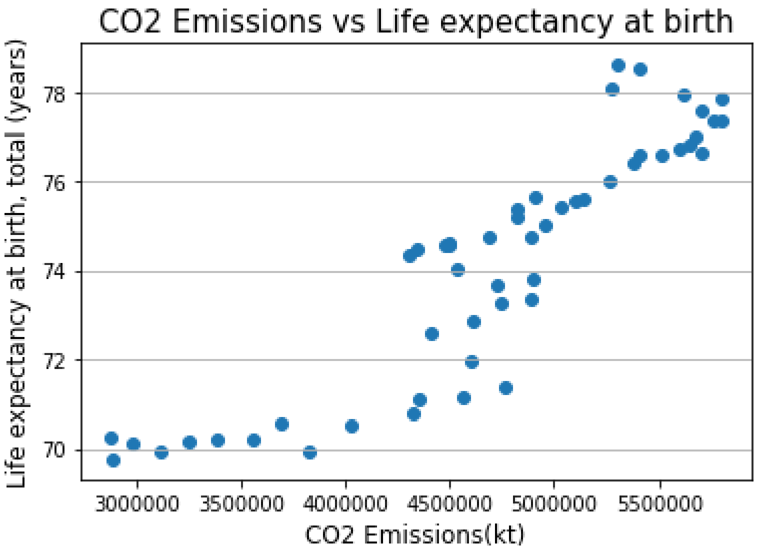

```
The correlation between CO2 Emissions and Fertility Rate is: -0.752

<Figure size 432x288 with 0 Axes>
```

4. Scatter Plot of CO2 Emissions(kt) vs Life expectancy at birth, total (years)

Code below is to `create a scatter plot` and to `save` it as an `image file` to use in the presentation.

In [26]:

```
fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

x = 'CO2 Emissions(kt)'
y = 'Life expectancy at birth, total (years)'

a = 'CO2 Emissions'
b = 'Life expectancy at birth'
axis.yaxis.grid(True)
axis.set_title(a+' vs '+b,fontsize=15)
axis.set_xlabel(x ,fontsize=12)
axis.set_ylabel(y ,fontsize=12)

X = df3['Value'].values
Y = hdf4['Value'].values

axis.scatter(X, Y)
plt.show()
plt.savefig('CO2 vs Life Expectancy at birth.png', bbox_inches='tight')

column_1 = df3["Value"]
column_2 = hdf4["Value"]
correlation = column_1.corr(column_2)

print('The correlation between '+a+' and '+b+' is: '+str(round(correlation, 3)))
```



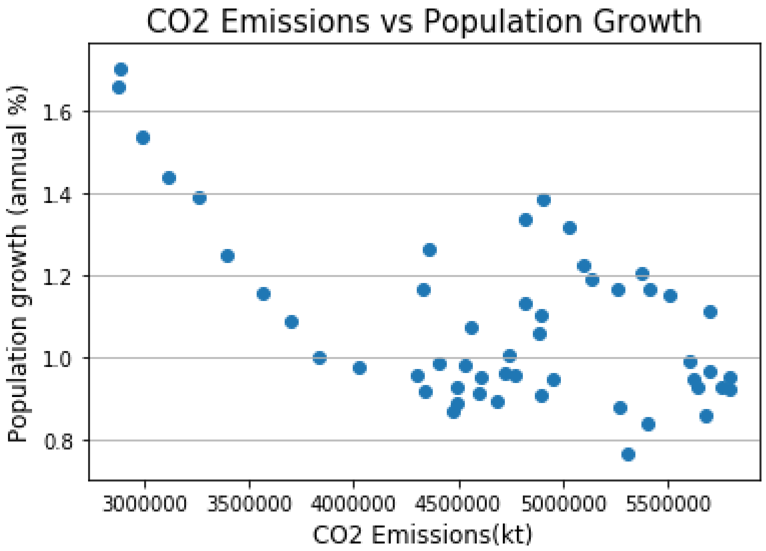

```
The correlation between CO2 Emissions and Life expectancy at birth is: 0.899

<Figure size 432x288 with 0 Axes>
```

5. Scatter Plot of CO2 Emissions(kt) vs Population growth (annual %)

Code below is to `create a scatter plot` and to `save` it as an `image file` to use in the presentation.

In [27]:

```
fig, axis = plt.subplots()
# Grid lines, Xticks, Xlabel, Ylabel

x = 'CO2 Emissions(kt)'
y = 'Population growth (annual %)'

a = 'CO2 Emissions'
b = 'Population Growth'
axis.yaxis.grid(True)
axis.set_title(a+' vs '+b,fontsize=15)
axis.set_xlabel(x ,fontsize=12)
axis.set_ylabel(y ,fontsize=12)

X = df3['Value'].values
Y = hdf5['Value'].values

axis.scatter(X, Y)
plt.show()
plt.savefig('CO2 vs Population Growth.png', bbox_inches='tight')

column_1 = df3["Value"]
column_2 = hdf5["Value"]
correlation = column_1.corr(column_2)

print('The correlation between '+a+' and '+b+' is: '+str(round(correlation, 3)))
```




```
The correlation between CO2 Emissions and Population Growth is: -0.591
```

```
<Figure size 432x288 with 0 Axes>
```

Conclusion

We can finally conclude by saying that growing `CO2 Emissions` has a

1. `very strong negative impact on Birth rate, crude (per 1,000 people)`
2. `negligible impact on Mortality rate, infant (per 1,000 live births)`
3. `strong negative impact on Fertility rate, total (births per woman)`
4. `negligible impact on Life expectancy at birth, total (years)`
5. `mild negative impact on Population growth (annual %)`