Investigate_a_Dataset

October 7, 2020

1 Project 2: Investigating Data From Around the World

1.1 Introduction - Gapminder Data

In the below analysis I'll be driving into some topics that sparked my interest. The data from Gapminder was very extensive with lots of datasets to be explored but I was able to narrow it down to a few topics. I would like to preface, since each csv file downloaded from Gapminder had varying levels of completion and avaiable years showing data I can't combine all my data into one dataset for all questions. Instead, I'll be analying, wrangling and cleaning the data to create specific dataframes for multiple research quesitons. Each questions will be broken into sections: question, explanation/information, cleaning/wrangling, anaylsis and synapsis.

1.2 Project Introduction

Throughout this project our questioning will revolve around 2 distinct variables: total murders per year and life expectancy. Part 1 (Q1 & Q2) help us understand the correlation between total murders and population. We will examine this topic further by representing the most dangerous countries by violent crime rates as a proportion to population size and population density. Part 2 (Q3 & Q4) we will understand how average life expectancy changes throughout history and if income per capita or health spend based of GDP has an affect towarded more prolonged life. Finally, I we will end the project with a final conclusion summarizing our findings and data limitations.

Here are the 4 research questions we are about to explore: 1. Where are the most dangerous places to live? 2. How does population density effect violent murder rates? 3. Does average income per person effect life expectancy by country and which country had the greatest improvement in life expectancy? 4. How health spend effect life expectancy?

1.3 Table of Contents

Final Conclusion

```
In [1]: #import packages - I have used these imports at the start of most questions as well just

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

Dataset Overview **NOTE:** All of these datasets are columnized by year and organized vertically by country. The data points correspond to a country for a one year period. Also, all datasets have variety of years and provided countries.

What the data values represent: **income.csv** - Income per person (GDP per capita, PPP inflation-adjusted) **life_exp.csv** - Average life expectancy in years **murders.csv** - Total murders **total_health_spend.csv** - Total health spend (% of total GDP) **pop_density.csv** - Average number of people per square km of land in country **populations_csv** - Total population **gini.csv** - Gini coefficient per year (Higher number greater income inequality). Used for example

```
In [2]: #How I read in all datasets throughout the project
        gini_df = pd.read_csv('gini.csv')
        income_df = pd.read_csv('income.csv')
        life_exp_df = pd.read_csv('life_exp.csv')
        murders_df = pd.read_csv('murders.csv')
        pop_density_df = pd.read_csv('pop_density.csv')
        pop_df = pd.read_csv('population.csv')
        health_df = pd.read_csv('total_health_spend.csv')
```

Largest Challenge in Project

All the datasets from Gapminder organized their data using years as columns for each corresponging country and listed irrelevant future years in some dataframes. In order to anaylze the data properly over time I needed to consolidate all the year columns into one 'year' column and eliminate the irrelevant years. I did this by using drop function for irrelevant years and the melt function to organize my data as such: country, year, data1, data2, etc.

Below are the corresponding steps needed to complete the melt and drop function. A method I used multiple times throuhgout the project.

```
In [3]: #Understand data structure - gives me what years I need to drop
        gini_df.head()
```

```
Out[3]:        country  1800  1801  1802  1803  1804  1805  1806  1807  1808  ...   \
        0  Afghanistan  30.5  30.5  30.5  30.5  30.5  30.5  30.5  30.5  30.5  ...
        1      Albania  38.9  38.9  38.9  38.9  38.9  38.9  38.9  38.9  38.9  ...
```

```
2      Algeria  56.2  56.2  56.2  56.2  56.2  56.2  56.2  56.2  56.2  ...
3      Andorra  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0  ...
4       Angola  57.2  57.2  57.2  57.2  57.2  57.2  57.2  57.2  57.2  ...

   2031  2032  2033  2034  2035  2036  2037  2038  2039  2040
0  36.8  36.8  36.8  36.8  36.8  36.8  36.8  36.8  36.8  36.8
1  29.0  29.0  29.0  29.0  29.0  29.0  29.0  29.0  29.0  29.0
2  27.6  27.6  27.6  27.6  27.6  27.6  27.6  27.6  27.6  27.6
3  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0
4  42.6  42.6  42.6  42.6  42.6  42.6  42.6  42.6  42.6  42.6

[5 rows x 242 columns]
```

In [4]:
```
gini_df.shape
```

Out[4]:
```
(195, 242)
```

In [5]:
```
#Get rid of years above 2020
col = range(2021, 2041)
for i in col:
    col_drop = str(i)
    gini_df.drop(col_drop, axis=1, inplace=True)
```

In [6]:
```
#Makes sure code ran properly and dataset is updated
gini_df.head()
```

Out[6]:
```
       country  1800  1801  1802  1803  1804  1805  1806  1807  1808  ...   \
0  Afghanistan  30.5  30.5  30.5  30.5  30.5  30.5  30.5  30.5  30.5  ...
1      Albania  38.9  38.9  38.9  38.9  38.9  38.9  38.9  38.9  38.9  ...
2      Algeria  56.2  56.2  56.2  56.2  56.2  56.2  56.2  56.2  56.2  ...
3      Andorra  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0  ...
4       Angola  57.2  57.2  57.2  57.2  57.2  57.2  57.2  57.2  57.2  ...

   2011  2012  2013  2014  2015  2016  2017  2018  2019  2020
0  36.8  36.8  36.8  36.8  36.8  36.8  36.8  36.8  36.8  36.8
1  29.3  29.1  29.0  29.0  29.0  29.0  29.0  29.0  29.0  29.0
2  28.2  27.9  27.7  27.6  27.6  27.6  27.6  27.6  27.6  27.6
3  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0  40.0
4  42.7  42.6  42.6  42.6  42.6  42.6  42.6  42.6  42.6  42.6

[5 rows x 222 columns]
```

For more information on pd.melt

In [7]:
```
#Reorganize my dataset to make it more easily anaylzed columns: (country, year, gini)
gini_df2 = pd.melt(gini_df, id_vars='country', var_name='year', value_name='gini')

#Check function ran properly
gini_df2.head()
```

```
Out[7]:        country  year  gini
        0  Afghanistan  1800  30.5
        1      Albania  1800  38.9
        2      Algeria  1800  56.2
        3      Andorra  1800  40.0
        4       Angola  1800  57.2
```

```
In [8]: gini_df2.shape
```

```
Out[8]: (43095, 3)
```

```
In [9]: #Understand dataset
        income_df.head()
```

```
Out[9]:        country  1800  1801  1802  1803  1804  1805  1806  1807  1808  ...    \
        0  Afghanistan   603   603   603   603   603   603   603   603   603  ...
        1      Albania   667   667   667   667   667   668   668   668   668  ...
        2      Algeria   715   716   717   718   719   720   721   722   723  ...
        3      Andorra  1200  1200  1200  1200  1210  1210  1210  1210  1220  ...
        4       Angola   618   620   623   626   628   631   634   637   640  ...

            2031   2032   2033   2034   2035   2036   2037   2038   2039   2040
        0   2550   2600   2660   2710   2770   2820   2880   2940   3000   3060
        1  19400  19800  20200  20600  21000  21500  21900  22300  22800  23300
        2  14300  14600  14900  15200  15500  15800  16100  16500  16800  17100
        3  73600  75100  76700  78300  79900  81500  83100  84800  86500  88300
        4   6110   6230   6350   6480   6610   6750   6880   7020   7170   7310

        [5 rows x 242 columns]
```

```
In [10]: #Drop years after 2020
         col1 = range(2021, 2041)
         for i in col1:
             col_drop = str(i)
             income_df.drop(col_drop, axis=1, inplace=True)

         #Melt the columns to rows
         income_df_updated  = pd.melt(income_df, id_vars='country', var_name='year', value_name=
```

```
In [11]: #Check updates
         income_df_updated.head()
```

```
Out[11]:        country  year  income
         0  Afghanistan  1800     603
         1      Albania  1800     667
         2      Algeria  1800     715
         3      Andorra  1800    1200
         4       Angola  1800     618
```

Research Question 1: Where are the most dangerous places to live?

```
In [12]: #Import packages:
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         % matplotlib inline
```

```
In [13]: #Datasets needed:
         murders_df = pd.read_csv('murders.csv')
         pop_df = pd.read_csv('population.csv')
```

1.3.1 Explanation

I'm using total murders as the metric to decide how dangerous a country is. If there is a higher murder count in a give country than we can assume it is more dangerous. Of course, we can argue that if the population is greater than total murders may be higher in comparison to smaller countries. Therefore, I'll create an additional column using murders in proportion to the countries population.

1.3.2 Understanding Data Layout

```
In [14]: #Understand dataframe layout - we immediately see some irrelevant future years
         murders_df.head()
```

```
Out[14]:        country     1990     1991     1992     1993     1994     1995     1996  \
         0  Afghanistan  2070.00  2200.00  2380.00  2600.00  2830.00  3020.00  3160.00
         1      Albania   160.00   182.00   201.00   221.00   239.00   267.00   295.00
         2      Algeria   377.00   382.00   391.00   400.00   410.00   421.00   432.00
         3      Andorra     0.48     0.51     0.54     0.55     0.55     0.53     0.51
         4       Angola   527.00   532.00   543.00   569.00   598.00   608.00   582.00

              1997     1998   ...        2007     2008     2009     2010     2011  \
         0  3270.0  3350.00   ...     4910.00  4960.00  4990.00  4940.00  5020.00
         1   327.0   338.00   ...       82.70    77.50    67.50    68.40    68.50
         2   452.0   468.00   ...      437.00   441.00   445.00   447.00   451.00
         3     0.5     0.49   ...        0.52     0.52     0.53     0.54     0.54
         4   582.0   667.00   ...      904.00   933.00   958.00   978.00   990.00

               2012     2013     2014     2015     2016
         0  5190.00  5560.00  5820.00  6060.00  6270.00
         1    68.50    68.70    68.90    69.20    69.50
         2   457.00   465.00   474.00   472.00   471.00
         3     0.54     0.55     0.55     0.55     0.55
         4  1010.00  1030.00  1050.00  1080.00  1090.00

         [5 rows x 28 columns]
```

```
In [15]: #Compare shapes to understand which dataframe we have to match to the other
         murders_df.shape
```

Out[15]: (187, 28)

In [16]: pop_df.shape

Out[16]: (195, 302)

We notice, murders dataset has a smaller range of years (27 vs 301) and listed countries (187 vs 195) than popluation. ### Cleaning/Wrangling Data

Steps: 1. Remove irrelevant years from poplulation to match murders dataframe 2. Melt both dataframes for easier analysis 3. Merge dataframes only keeping similar countries 4. Check for missing or null values

In [17]:
```
#Drop years - need 1990 - 2016
col = np.r_[1800:1990 , 2017:2101]
for i in col:
    col_drop = str(i)
    pop_df.drop(col_drop, axis=1, inplace=True)

#Check for code completion
pop_df.head()
```

Out[17]:
```
       country      1990      1991      1992      1993      1994      1995  \
0  Afghanistan  12400000  13300000  14500000  15800000  17100000  18100000
1      Albania   3290000   3280000   3250000   3200000   3150000   3110000
2      Algeria  25800000  26400000  27000000  27600000  28200000  28800000
3      Andorra     54500     56700     58900     61000     62700     63900
4       Angola  11800000  12200000  12700000  13100000  13500000  13900000

       1996      1997      1998    ...         2007      2008      2009  \
0  18900000  19400000  19700000    ...     27100000  27700000  28400000
1   3100000   3100000   3110000    ...      3030000   3000000   2970000
2  29300000  29700000  30200000    ...     34200000  34700000  35300000
3     64400     64300     64100    ...        82700     83900     84500
4  14400000  14900000  15400000    ...     20900000  21700000  22500000

       2010      2011      2012      2013      2014      2015      2016
0  29200000  30100000  31200000  32300000  33400000  34400000  35400000
1   2950000   2930000   2910000   2900000   2900000   2890000   2890000
2  36000000  36700000  37400000  38100000  38900000  39700000  40600000
3     84500     83700     82400     80800     79200     78000     77300
4  23400000  24200000  25100000  26000000  26900000  27900000  28800000

[5 rows x 28 columns]
```

In [18]:
```
#Melt both datasets so we can join
murders_melt_df = pd.melt(murders_df, id_vars='country', var_name='year', value_name='t

pop_melt_df = pd.melt(pop_df, id_vars='country', var_name='year', value_name='total_pop
```

In [19]:
```
#Check to make sure there are 3 columns
murders_melt_df.shape
```

Out[19]:
```
(5049, 3)
```

In [20]:
```
pop_melt_df.shape
```

Out[20]:
```
(5265, 3)
```

In [21]:
```
#Merge datasets and check for null values
violence_df = pd.merge(pop_melt_df, murders_melt_df, on=['country', 'year'], how='right
violence_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5049 entries, 0 to 5048
Data columns (total 4 columns):
country          5049 non-null object
year             5049 non-null object
total_pop        5049 non-null int64
total_murders    5049 non-null float64
dtypes: float64(1), int64(1), object(2)
memory usage: 197.2+ KB
```

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

Out[22]:

	country	year	total_pop	total_murders
0	Afghanistan	1990	12400000	2070.00
1	Albania	1990	3290000	160.00
2	Algeria	1990	25800000	377.00
3	Andorra	1990	54500	0.48
4	Angola	1990	11800000	527.00

According to the above info and head functions we can see that their are no null values and the dataframes are combine appropriately.

1.3.3 Analysis

In order to compare violent murders and poplulation throughout time I need to group our data points by country and find the mean murders value. This will organize the data allowing me to simply compare total murders based on country. **Note:** Normally, I might create different sections of time to see how murders and population has changed overtime in comparison to countries. Since we are only using a 26 year time span here I decided not to. We will see sectioned time eras later in project

In [23]:
```
#This is a global function used to eliminate scientific notation. Also allows multiple
pd.set_option('display.float_format', lambda x: '%.5f' %x)

#Group based on country and find mean from 1990 - 2016
violence_mean_df = violence_df.groupby('country', as_index=False).mean().sort_values(by
#Top 10 countries with highest
violence_mean_df.head(10)
```

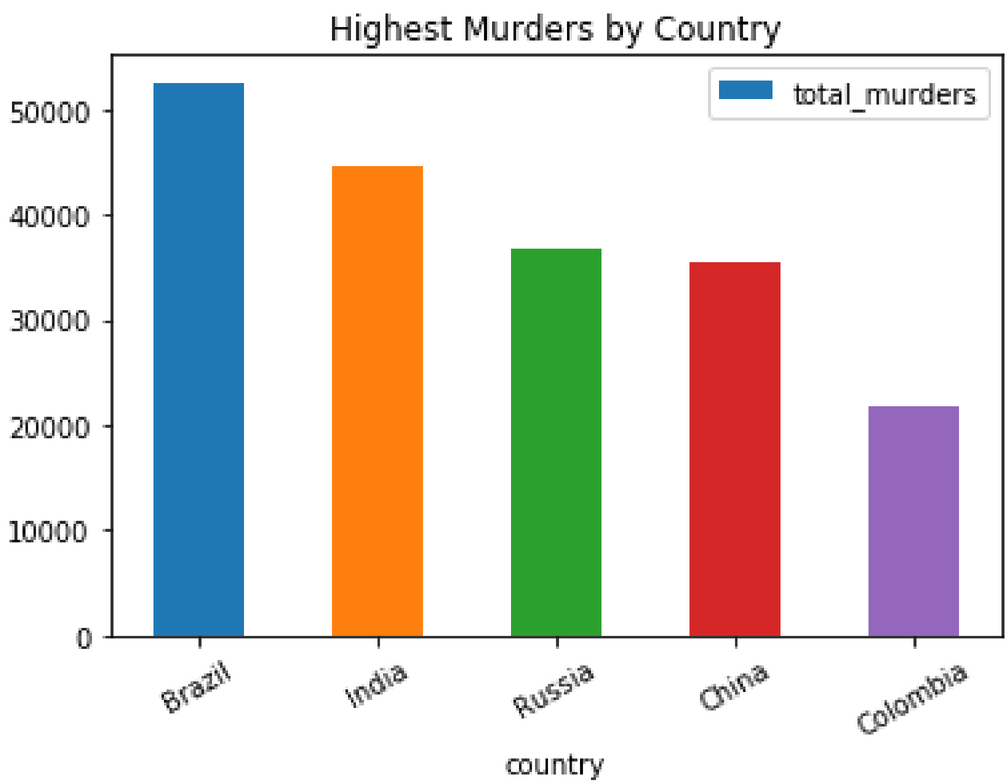
Out[23]:

```
            country          total_pop  total_murders
23           Brazil   180074074.07407    52555.55556
75            India  1107481481.48148    44740.74074
137          Russia   145555555.55556    36651.85185
35            China  1308888888.88889    35429.62963
36         Colombia    41111111.11111    21848.14815
151    South Africa    46681481.48148    20481.48148
178   United States   288814814.81481    19081.48148
107          Mexico   103488888.88889    16796.29630
132     Philippines    82848148.14815    11578.88889
182       Venezuela    25370370.37037     8288.88889
```

In [24]:

```
#Quick visual representation of countries with highest total murders
violence_mean_df.head().plot(x='country', y='total_murders', kind='bar', title='Highest
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7f64d24613c8>



As mentioned before, popluation of the above countries is much higher than other countries. We can argue that of course there will be more murders merely because there is a greater popluation, all other things held constant.

How to Fix: We create a column in table using murders in proportion to countries population (total murders / total population)

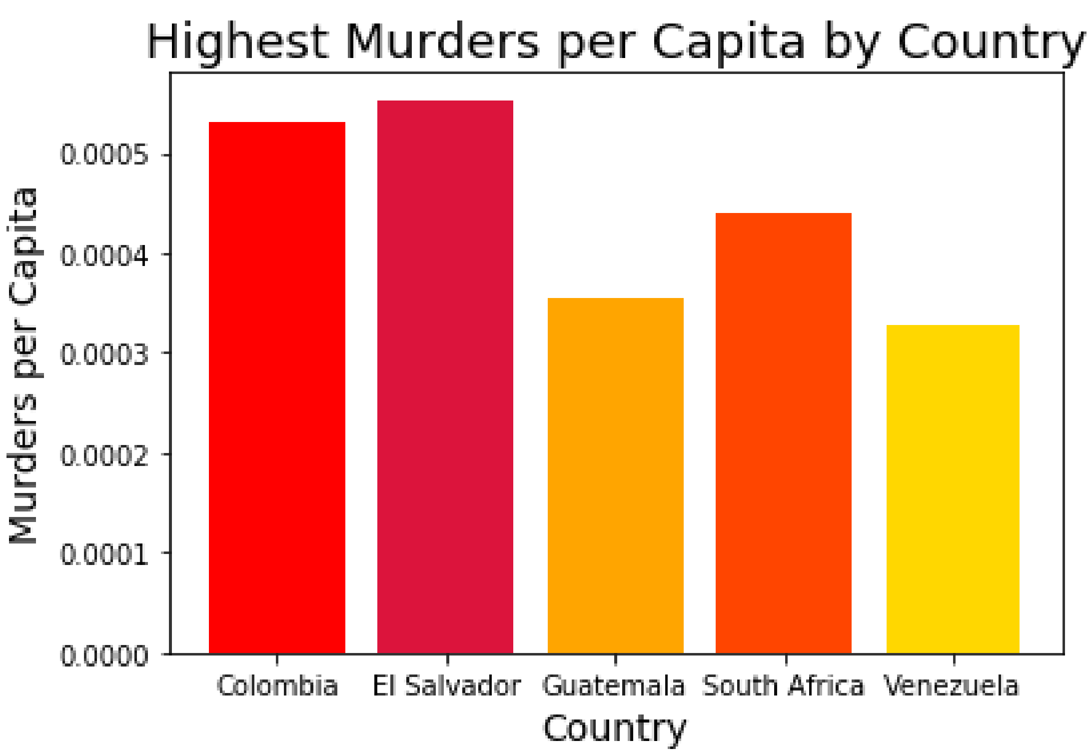
In [25]:
```python
#Let's now take into consideration popluation
violence_mean_df['murders_per_capita'] = violence_mean_df['total_murders'] / violence_m

#Check for proper code completion and sort to see top 10 coutries with highest murder r
violence_mean_df.sort_values(by='murders_per_capita', ascending=False).head(10)
```

Out[25]:

	country	total_pop	total_murders	murders_per_capita
52	El Salvador	5925925.92593	3276.29630	0.00055
36	Colombia	41111111.11111	21848.14815	0.00053
151	South Africa	46681481.48148	20481.48148	0.00044
67	Guatemala	12658888.88889	4494.44444	0.00036
182	Venezuela	25370370.37037	8288.88889	0.00033
93	Lesotho	1964074.07407	595.92593	0.00030
23	Brazil	180074074.07407	52555.55556	0.00029
72	Honduras	7101481.48148	2064.81481	0.00029
137	Russia	145555555.55556	36651.85185	0.00025
160	Swaziland	1002222.22222	208.66667	0.00021

In [26]:
```python
#Cleaner visual representation of data answering our initial question
x = violence_mean_df.sort_values(by='murders_per_capita', ascending=False)['country'].h
y = violence_mean_df.sort_values(by='murders_per_capita', ascending=False)['murders_per
plt.bar(x, y, color=['Crimson', 'Red', 'Orangered', 'Orange', 'Gold'])
plt.xlabel('Country', fontsize=14)
plt.ylabel('Murders per Capita', fontsize=14)
plt.title('Highest Murders per Capita by Country', fontsize=18)
```

Out[26]: Text(0.5,1,'Highest Murders per Capita by Country')



1.3.4 Q1 Synapsis

Based on the murders per capita and only taking into consideration the countries that we had data for in the above dataframes provided by Gapminder, Colombia, El Salvador, Guatemala, South Africa and Venezuela are the most dangerous places to live. Of course, this is only based on a few perameters and I'm sure there are many other factors that play into which country is most dangerous.

Possibly popluation density rather than total population?

Research Question 2: How does population density effect violent murder rates?

This is a continuation of above question so we're able to use the already cleaned and wrangled data. All we need to do is clean/wrangle and then combine population density to total murders.

1.3.5 Explanation

Density is average number of people in square km of land. The reason I'm interested in population density is what if a smaller country with a very large density has a correlation to total murders in the country. We can show correlation visually by using a scatter plot. If total murders increase as population density increases then there is a correlation between the variables.

1.3.6 Clean/Wrangling

In [27]:
```
# Continuation of above research question. Now lets add population density to the dataf
pop_density_df = pd.read_csv('pop_density.csv')
pop_density_df.head()
```

Out[27]:
```
       country      1950      1951      1952      1953      1954      1955      1956  \
0  Afghanistan  11.90000  12.00000  12.20000  12.30000  12.50000  12.70000  12.90000
1      Albania  46.10000  47.00000  48.00000  49.20000  50.50000  51.80000  53.30000
2      Algeria   3.73000   3.79000   3.86000   3.93000   4.01000   4.10000   4.20000
3      Andorra  13.20000  14.20000  15.40000  16.70000  18.20000  19.60000  21.20000
4       Angola   3.65000   3.70000   3.78000   3.87000   3.96000   4.05000   4.12000

      1957      1958    ...          2091       2092       2093       2094  \
0 13.10000  13.30000    ...     117.00000  117.00000  117.00000  117.00000
1 54.80000  56.30000    ...      48.50000   47.50000   46.50000   45.50000
2  4.31000   4.41000    ...      29.60000   29.60000   29.60000   29.60000
3 22.90000  24.70000    ...     134.00000  134.00000  134.00000  134.00000
4  4.19000   4.26000    ...     135.00000  136.00000  138.00000  140.00000

       2095       2096       2097       2098       2099       2100
0 116.00000  116.00000  116.00000  115.00000  115.00000  115.00000
1  44.50000   43.50000   42.50000   41.60000   40.60000   39.70000
2  29.70000   29.70000   29.70000   29.70000   29.70000   29.70000
3 133.00000  133.00000  133.00000  133.00000  133.00000  133.00000
4 142.00000  144.00000  146.00000  147.00000  149.00000  151.00000
```

```
[5 rows x 152 columns]
```

```
In [28]: #Delete none used years (1950 - 1989 & 2017 - 2100)
         col = np.r_[1950:1990, 2017:2101]
         for i in col:
             col_drop = str(i)
             pop_density_df.drop(col_drop, axis=1, inplace=True)

         #Melt the columns to rows
         pop_density_melt_df = pd.melt(pop_density_df, id_vars='country', var_name='year', value


         #Merge into violence_df
         violence_density_df = pd.merge(violence_df, pop_density_melt_df, on=['country', 'year']

         #Adding murders_per_captia for fun of comparison
         violence_density_df['murders_per_capita'] = violence_density_df['total_murders'] / viol

         #Check for null values and shape - should be no null and 5049 items
         violence_density_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5049 entries, 0 to 5048
Data columns (total 6 columns):
country               5049 non-null object
year                  5049 non-null object
total_pop             5049 non-null int64
total_murders         5049 non-null float64
density               5049 non-null float64
murders_per_capita    5049 non-null float64
dtypes: float64(3), int64(1), object(2)
memory usage: 276.1+ KB
```

```
In [29]: #double check data layout
         violence_density_df.head()
```

Out[29]:

	country	year	total_pop	total_murders	density	murders_per_capita
0	Afghanistan	1990	12400000	2070.00000	19.00000	0.00017
1	Albania	1990	3290000	160.00000	120.00000	0.00005
2	Algeria	1990	25800000	377.00000	10.80000	0.00001
3	Andorra	1990	54500	0.48000	116.00000	0.00001
4	Angola	1990	11800000	527.00000	9.50000	0.00004

1.3.7 Analysis

```
In [30]: #Group data by country and find the mean over time. Again, we are only working 26 year
         violence_density_mean = violence_density_df.groupby('country', as_index=False).mean()
```

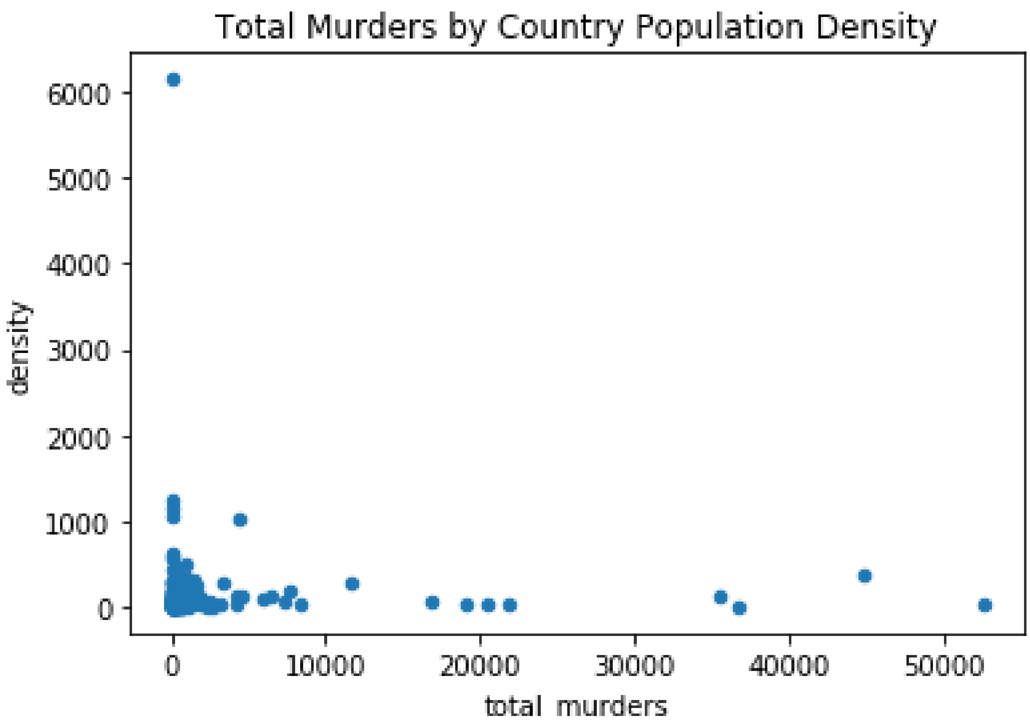
```
#Dataframe sorted by top density
violence_density_mean.sort_values(by='density', ascending=False).head()
```

Out[30]:

	country	total_pop	total_murders	density	murders_per_capita
146	Singapore	4306296.29630	28.29630	6151.48148	0.00001
103	Malta	398962.96296	5.55333	1246.29630	0.00001
12	Bahrain	880666.66667	17.02593	1157.81481	0.00002
101	Maldives	317629.62963	3.14963	1059.59259	0.00001
13	Bangladesh	132814814.81481	4332.22222	1020.14815	0.00003

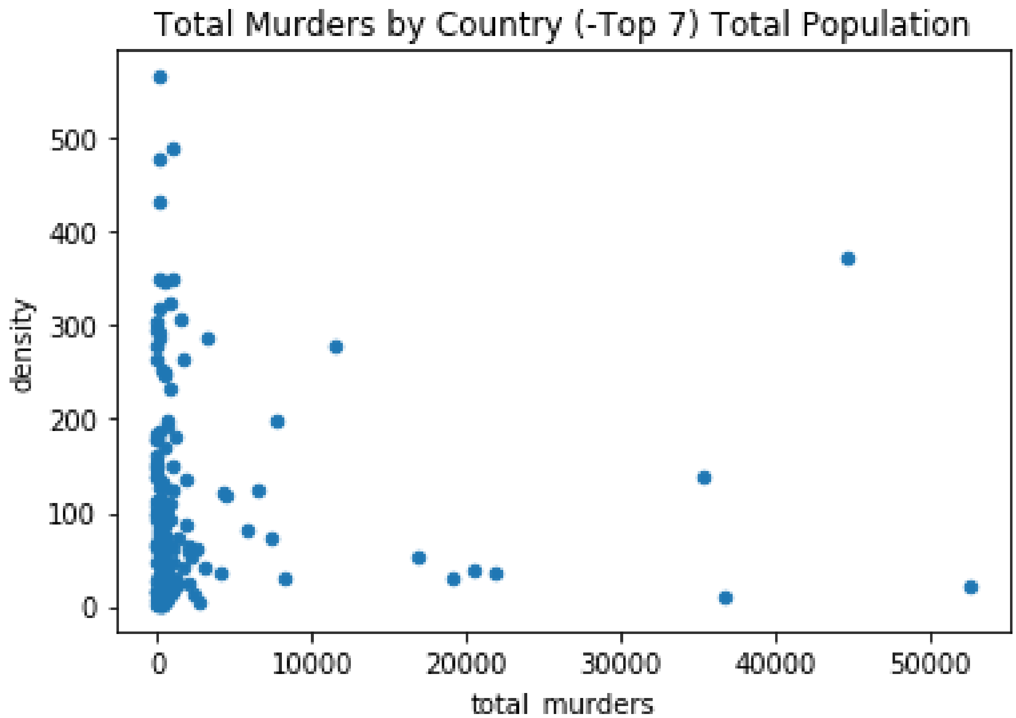
In [31]:
```
#Create a scatter plot to show comparison
violence_density_mean.sort_values(by='density', ascending=False).plot(x='total_murders'
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x7f64d24815c0>



In [32]:
```
#I removed the top 7 densest countries becasue they were outliners and screwing the gra
violence_density_mean.sort_values(by='density', ascending=False).tail(180).plot(x='tota
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7f64cfb9c630>



In order to be absolute certain, I will use the .corr function with the Pearson method the find the correlation coefficient between total_murders and density.

```
In [33]: column_1 = violence_density_mean["total_murders"]
         column_2 = violence_density_mean["density"]
         correlation = column_1.corr(column_2)
         print(correlation * 100)
```

```
-2.54509891184
```

1.3.8 Q2 Synapsis

There is no correlation to murders and population density. Singapore is a great example. Singapore has the highest density for popluation but has one of the lowest violent murder rates per capita (see below - murder per capita 55X lower than Colombia and density of 166X higher).

Furthermore, there is only a -2.55% correlation between population density and total_murders between countries. Using Pearson's method coeffient we would need to see upwards of (-)70% correlation to make an argument for comparison.

Again, the population density is based on the square km area of the entire country. It would probably be a better comparison if we had data for top metropolitan areas in all countries as some countries have a ton of uninhabited area.

```
In [34]: violence_density_mean.query('country == "Singapore" | country == "Colombia"')
```

```
Out[34]:        country       total_pop  total_murders    density  murders_per_capita
        36    Colombia 41111111.11111    21848.14815   37.03333             0.00055
        146  Singapore  4306296.29630       28.29630 6151.48148             0.00001
```

Research Question 3: Does average income per person effect life expectancy by country and which country had the greatest improvement in life expectancy?

1.3.9 Information

> **What is PPP?** PPP or Purchasing Power Parity is a way to compare the purchasing power from one conutry to another. This is also known as international currency and the unit being used in income.csv file. **How do we convert PPP to USD?** Well, we don't. The PPP is based off the purchasing power from other countries to the United States using the USD as a reference. Since we'd be comparing USD to USD the ratio from PPP to USD is 1/1.

1.3.10 Explanation

I was very curious as to how income effects the life expectancy in countries. Below I will explore this more but here is a bit of an overview as the dataframes are a bit more extensive. > As I explored the dataframes I was able to put together a greater range of years to compare. Meaning that I'm not going to be able to take a mean over the entire time period as the data maybe skewed. **To fix this** I created 50 year segments and created another table to better understand life expectancy overtime.

Furthermore, I would like to preface that the years of life expectancy in eariler years was very low and makes me question the integrity of the data in many countries. We are going to assume for the sake of the assignment that the data from Gapminder is percise.

```
In [35]: #Import libraries
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         % matplotlib inline
```

```
In [36]: #Datasets needed:
         income_df = pd.read_csv('income.csv')
         life_exp_df = pd.read_csv('life_exp.csv')
```

```
In [37]: #Understand data layout
         income_df.head()
```

```
Out[37]:        country  1800  1801  1802  1803  1804  1805  1806  1807  1808  ...     \
         0  Afghanistan   603   603   603   603   603   603   603   603   603  ...
         1      Albania   667   667   667   667   667   668   668   668   668  ...
         2      Algeria   715   716   717   718   719   720   721   722   723  ...
         3      Andorra  1200  1200  1200  1200  1210  1210  1210  1210  1220  ...
         4       Angola   618   620   623   626   628   631   634   637   640  ...

            2031   2032   2033   2034   2035   2036   2037   2038   2039   2040
```

```
0   2550   2600   2660   2710   2770   2820   2880   2940   3000   3060
1  19400  19800  20200  20600  21000  21500  21900  22300  22800  23300
2  14300  14600  14900  15200  15500  15800  16100  16500  16800  17100
3  73600  75100  76700  78300  79900  81500  83100  84800  86500  88300
4   6110   6230   6350   6480   6610   6750   6880   7020   7170   7310

[5 rows x 242 columns]
```

In [38]:
```
life_exp_df.head()
```

Out[38]:
```
       country     1800     1801     1802     1803     1804     1805     1806  \
0  Afghanistan 28.20000 28.20000 28.20000 28.20000 28.20000 28.20000 28.10000
1      Albania 35.40000 35.40000 35.40000 35.40000 35.40000 35.40000 35.40000
2      Algeria 28.80000 28.80000 28.80000 28.80000 28.80000 28.80000 28.80000
3      Andorra      nan      nan      nan      nan      nan      nan      nan
4       Angola 27.00000 27.00000 27.00000 27.00000 27.00000 27.00000 27.00000

      1807     1808   ...       2091     2092     2093     2094     2095  \
0 28.10000 28.10000   ...   76.50000 76.60000 76.70000 76.90000 77.00000
1 35.40000 35.40000   ...   87.40000 87.50000 87.60000 87.70000 87.80000
2 28.80000 28.80000   ...   88.30000 88.40000 88.50000 88.60000 88.70000
3      nan      nan   ...        nan      nan      nan      nan      nan
4 27.00000 27.00000   ...   78.70000 78.90000 79.00000 79.10000 79.30000

      2096     2097     2098     2099     2100
0 77.10000 77.30000 77.40000 77.50000 77.70000
1 87.90000 88.00000 88.10000 88.20000 88.30000
2 88.80000 88.90000 89.00000 89.10000 89.20000
3      nan      nan      nan      nan      nan
4 79.40000 79.50000 79.70000 79.80000 79.90000

[5 rows x 302 columns]
```

In [39]:
```
#Understand and compare shape
income_df.shape
```

Out[39]:
```
(193, 242)
```

In [40]:
```
life_exp_df.shape
```

Out[40]:
```
(187, 302)
```

1.3.11 Clean and Wrangle

Steps are exactly the same as previous sections as dataframe layout identical

In [41]:
```
#Remove all years from both life_exp and income so they match.

#Removing years for life_exp
```

```
col = np.r_[2021:2101]
for i in col:
    col_drop = str(i)
    life_exp_df.drop(col_drop, axis=1, inplace=True)

#Removing years for income
col = np.r_[2021:2041]
for i in col:
    col_drop = str(i)
    income_df.drop(col_drop, axis=1, inplace=True)

#Melt the colums into rows
income_melt_df = pd.melt(income_df, id_vars='country', var_name='year', value_name='inc
life_exp_melt_df = pd.melt(life_exp_df, id_vars='country', var_name='year', value_name=
```

```
In [42]: #Compare shape of the dataframes to make sure there are 3 columns
         income_melt_df.shape
```

```
Out[42]: (42653, 3)
```

```
In [43]: life_exp_melt_df.shape
```

```
Out[43]: (41327, 3)
```

```
In [44]: #income has more countries so merge income to life_exp only keeping similar countries
         life_income_df = pd.merge(income_melt_df, life_exp_melt_df, on=['country', 'year'], how
         life_income_df.shape

         #In truth you could merge into smaller dataframe or do an inner merge here.
```

```
Out[44]: (41327, 4)
```

```
In [45]: #Check for null values
         life_income_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41327 entries, 0 to 41326
Data columns (total 4 columns):
country              41327 non-null object
year                 41327 non-null object
income_per_capita    41327 non-null int64
exp_years_lived      40808 non-null float64
dtypes: float64(1), int64(1), object(2)
memory usage: 1.6+ MB
```

After checking for null or missing data we find that exp_years_lived has lots of missing values. Let's explore more to better understand where the missing values are coming from.

```
In [46]: #Figure out where the missing data is in exp_years_lived.
         missing_df = life_income_df.query('exp_years_lived == "NaN"')
         missing_df.groupby('country', as_index=False).mean()
```

```
Out[46]:             country  income_per_capita  exp_years_lived
         0           Andorra         5240.80925              nan
         1          Dominica         1272.83237              nan
         2  Marshall Islands          816.12139              nan
```

```
In [47]: #Seems like its only in 3 different countries for practically all of their data points.
         a = ['Andorra', 'Dominica', 'Marshall Islands']
         for i in a:
             index_num = life_income_df[life_income_df['country'] == i].index
             life_income_df.drop(index_num, inplace=True)

         #Check again for missing data
         life_income_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 40664 entries, 0 to 41326
Data columns (total 4 columns):
country              40664 non-null object
year                 40664 non-null object
income_per_capita    40664 non-null int64
exp_years_lived      40664 non-null float64
dtypes: float64(1), int64(1), object(2)
memory usage: 1.6+ MB
```

```
In [48]: #Double check that countries have been dropped - dataframe should be empty
         life_income_df.query('country == "Andorra" | country == "Dominica" | country == "Marsha
```

```
Out[48]: Empty DataFrame
         Columns: [country, year, income_per_capita, exp_years_lived]
         Index: []
```

1.3.12 Analysis

In order to answer the questions properly, I need to break the years into smaller sections and combine into a seperate dataframe. I will do this by splitting into roughly 50 year segments and a more recent 20 year segment so I can find means in those time periods and see which countries have improved the most without worry to much about skewed data.

```
In [49]: #Used this for comparison when printing out the early - late dataframes
         life_income_df.groupby('country', as_index=False).mean().head()
```

```
Out[49]:                country  income_per_capita  exp_years_lived
         0         Afghanistan         1319.09955         35.30891
         1             Albania         2386.40724         47.20498
```

```
2             Algeria        4254.33032        41.22534
3              Angola        2254.69231        35.07421
4   Antigua and Barbuda      5102.78281        47.06787
```

In [50]:
```
#First, I want to understand how life expectancy has changed overtime
x = 'exp_years_lived'

#Removing timeframes from the life_income_df so we can combine into another df later
early_df = life_income_df.query('year < "1850"').groupby('country', as_index=False)[x].
mid_df = life_income_df.query('year >= "1850" & year < "1900"').groupby('country', as_i
midlate_df = life_income_df.query('year >= "1900" & year < "1950"').groupby('country',
late_df = life_income_df.query('year >= "1950" & year < "2000"').groupby('country', as_
current_df = life_income_df.query('year >= "2000"').groupby('country', as_index=False)[

#Check to make sure it worked
current_df.head()
```

Out[50]:
```
               country  exp_years_lived
0          Afghanistan         59.57143
1              Albania         77.08571
2              Algeria         76.22857
3               Angola         59.35714
4  Antigua and Barbuda         76.34762
```

In [51]:
```
#Change column names so when combine we can tell them apart
early_df.rename(columns={x : 'early_yrs'}, inplace=True)
mid_df.rename(columns={x : 'mid_yrs'}, inplace=True)
midlate_df.rename(columns={x : 'midlate_yrs'}, inplace=True)
late_df.rename(columns={x : 'late_yrs'}, inplace=True)
current_df.rename(columns={x : 'current_yrs'}, inplace=True)

#Check changes
mid_df.head()
```

Out[51]:
```
               country  mid_yrs
0          Afghanistan 28.09200
1              Albania 35.40000
2              Algeria 27.86400
3               Angola 27.58800
4  Antigua and Barbuda 33.58200
```

In [52]:
```
#Combine the time sections for average years lived for all countries
from functools import reduce
data_frames = [early_df, mid_df, midlate_df, late_df, current_df]
merge_df = reduce(lambda  left,right: pd.merge(left,right,on=['country'],
                                            how='outer'), data_frames)
#Check merge
merge_df.head()
```

```
Out[52]:                country  early_yrs  mid_yrs  midlate_yrs  late_yrs  current_yrs
         0          Afghanistan   27.96000 28.09200     30.47340  44.52000     59.57143
         1              Albania   35.40000 35.40000     37.92800  67.54200     77.08571
         2              Algeria   28.62400 27.86400     32.69600  61.01600     76.22857
         3               Angola   27.00000 27.58800     30.59200  44.91800     59.35714
         4  Antigua and Barbuda   33.50000 33.58200     40.52600  68.36600     76.34762
```

```
In [53]: #Add an improvement column by subtracting early from late and sort appropriately.
         merge_df['improvement'] = merge_df['current_yrs'] - merge_df['early_yrs']
         merge_df.sort_values(by='improvement', ascending=False).head(10)
```

```
Out[53]:          country  early_yrs  mid_yrs  midlate_yrs  late_yrs  current_yrs  \
         86        Kuwait   26.00000 26.10800     29.19400  68.86000     81.11905
         149  South Korea   25.80000 25.83800     33.19800  62.68600     80.32857
         151        Spain   29.50000 30.32600     46.00600  72.63600     81.63810
         79         Italy   29.70000 33.53000     49.98800  72.78600     81.79524
         116    Nicaragua   25.40000 25.54000     30.17000  59.62600     77.10476
         101        Malta   28.70000 32.26000     52.88000  71.52400     80.21429
         143    Singapore   31.84400 34.04600     39.47400  70.45800     82.74286
         75          Iran   25.60000 25.80200     28.10800  59.58800     75.43810
         168      Tunisia   27.06600 28.47000     32.32200  60.18000     76.80952
         78        Israel   32.00000 32.00000     36.37800  72.49800     81.29524

              improvement
         86      55.11905
         149     54.52857
         151     52.13810
         79      52.09524
         116     51.70476
         101     51.51429
         143     50.89886
         75      49.83810
         168     49.74352
         78      49.29524
```

Kuwait, South Korea, Spain, Italy and Nicaragua have the greatest improvement in life expectancy in the past 220 years based on the data given by Gapminder. Again, I used time segments to stear clear of recently or earlier skewed data. I believe this is a more appropriate representation of improvement in life expectation.

1.3.13 Analysis Cont.

Next, we need to tackle how income per person effects life expectancy. As discussed above, the figures have already been converted/are represented in USD. And again, income in average per person in the given country.

```
In [54]: life_income_df.head()
```

```
Out[54]:                country  year  income_per_capita  exp_years_lived
         0          Afghanistan  1800                603         28.20000
```

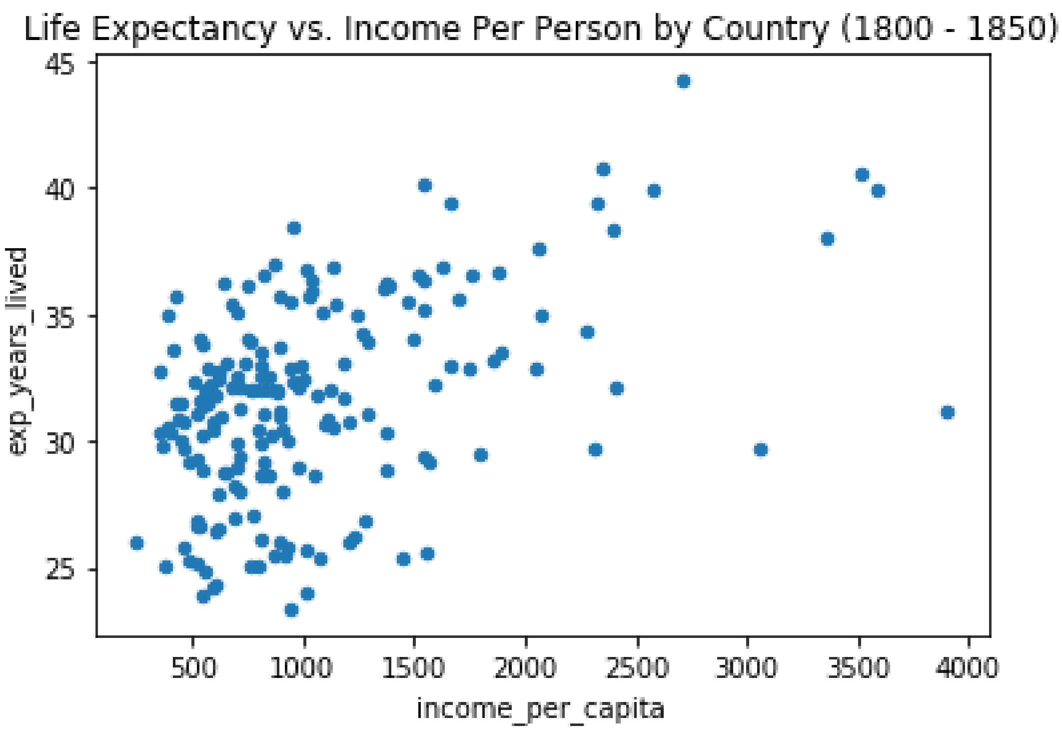
1	Albania	1800	667	35.40000
2	Algeria	1800	715	28.80000
4	Angola	1800	618	27.00000
5	Antigua and Barbuda	1800	757	33.50000

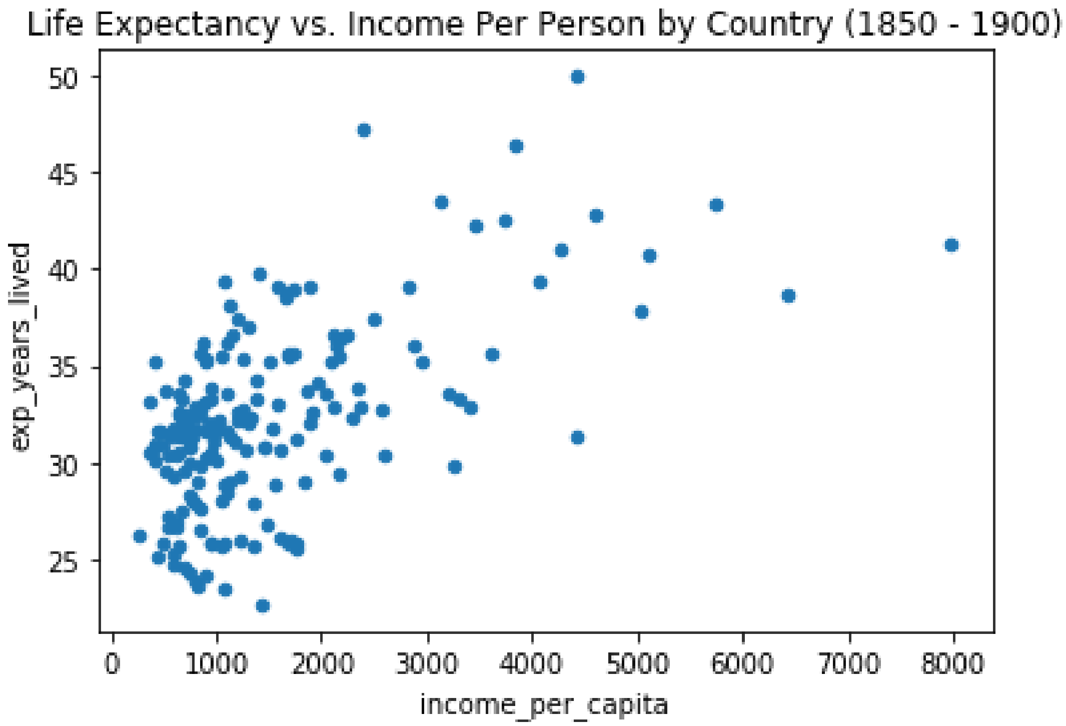
Let's create the same time segments again and compare income per person to life expectancy in all timeline to see how and if the correlation has changed overtime.

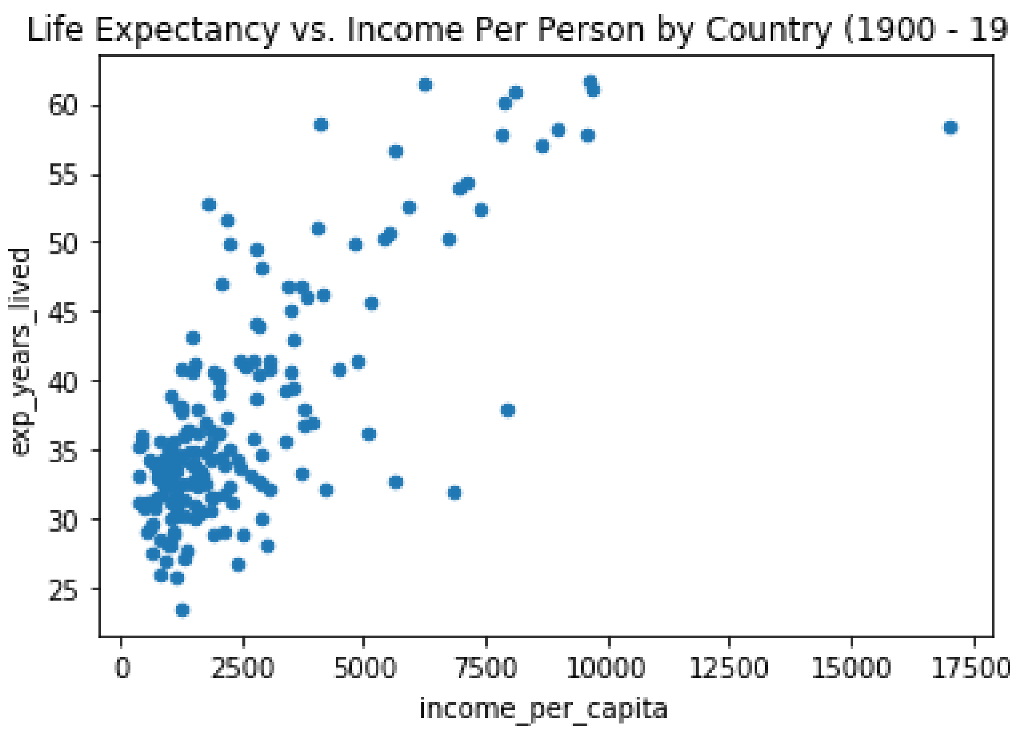
```
In [55]: #Create the timed segments so we can merge into one table.

         early_df = life_income_df.query('year < "1850"').groupby('country', as_index=False).mea
         mid_df = life_income_df.query('year >= "1850" & year < "1900"').groupby('country', as_i
         midlate_df = life_income_df.query('year >= "1900" & year < "1950"').groupby('country',
         late_df = life_income_df.query('year >= "1950"').groupby('country', as_index=False).mea
         current_df = life_income_df.query('year >= "2000"').groupby('country', as_index=False).


         #Create some scatter plots so we can compare different timeframes
         print('Below are scatter plots of expected years to live compared to income per person
         early_df.plot(x="income_per_capita", y="exp_years_lived", kind='scatter', title='Life E
         mid_df.plot(x="income_per_capita", y="exp_years_lived", kind='scatter', title='Life Exp
         midlate_df.plot(x="income_per_capita", y="exp_years_lived", kind='scatter', title='Life
         late_df.plot(x="income_per_capita", y="exp_years_lived", kind='scatter', title='Life Ex
         current_df.plot(x="income_per_capita", y="exp_years_lived", kind='scatter', title='Life
```

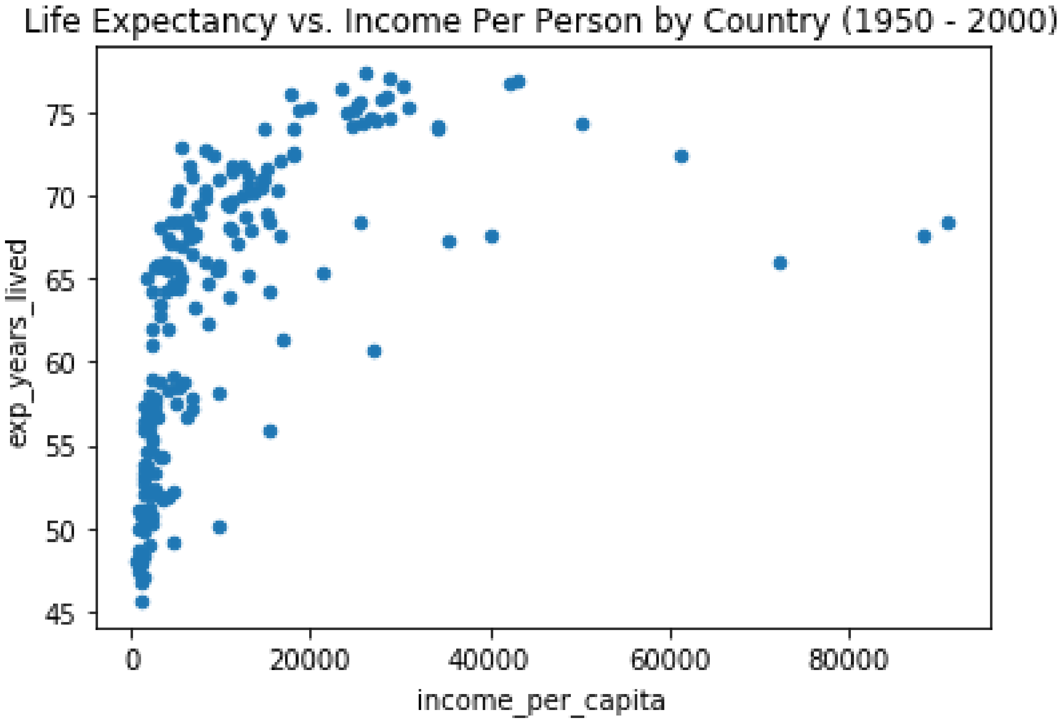
```
Below are scatter plots of expected years to live compared to income per person organized by cou
```

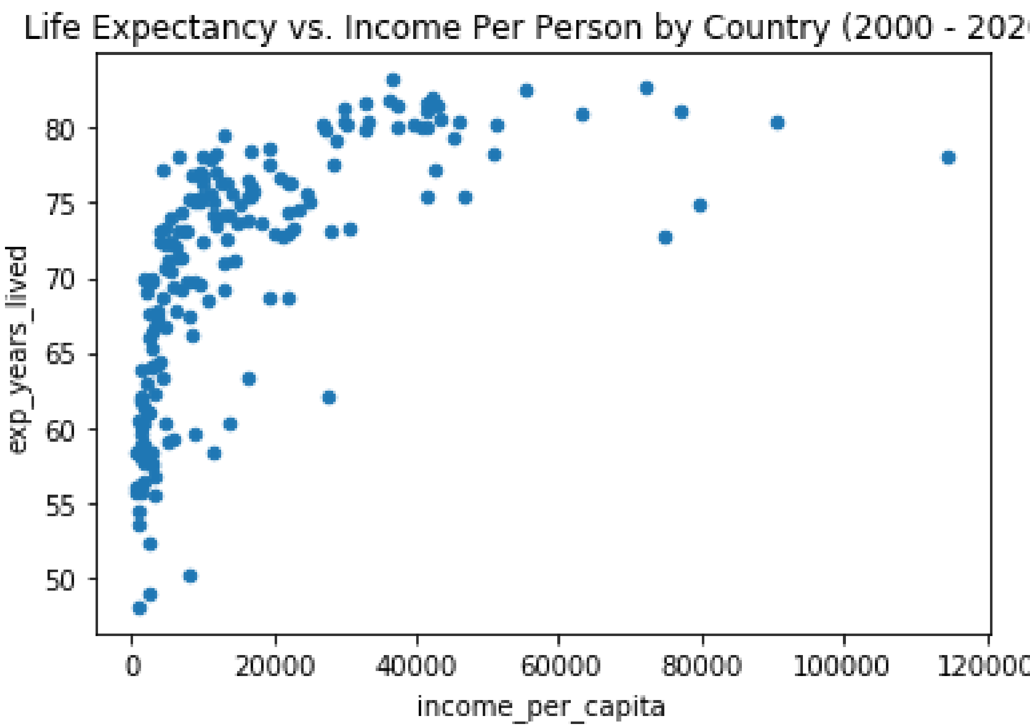
```
Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x7f64cf986eb8>
```




Life Expectancy vs. Income Per Person by Country (1850 - 1900)
exp_years_lived
income_per_capita
50
45
40
35
30
25
0
1000
2000
3000
4000
5000
6000
7000
8000


Life Expectancy vs. Income Per Person by Country (1900 - 1950)
exp_years_lived
income_per_capita
60
55
50
45
40
35
30
25
0
2500
5000
7500
10000
12500
15000
17500


Life Expectancy vs. Income Per Person by Country (1950 - 2000)
exp_years_lived
45
50
55
60
65
70
75
income_per_capita
0
20000
40000
60000
80000


Life Expectancy vs. Income Per Person by Country (2000 - 2020)
exp_years_lived
50
55
60
65
70
75
80
income_per_capita
0
20000
40000
60000
80000
100000
120000

After scanning the scatter plots it almost seems like the correlation between and income per person and longer life expectancy has become less and less correlated. To be sure lets use the Pearson correlation coefficient again on each timeline.

In [56]:
```
#Create an array of data for correlation coefficients
#NOTE: I had to give dataframes below names so I could append the names appropriately i
early_df.name = 'early'
mid_df.name = 'mid'
midlate_df.name = 'midlate'
late_df.name = 'late'
current_df.name = 'current'
df = [early_df, mid_df, midlate_df, late_df, current_df]
data = []
for i in df:
    column_1 = i["income_per_capita"]
    column_2 = i["exp_years_lived"]
    correlation = (column_1.corr(column_2)) * 100
    data.append([i.name, correlation])

#Use the array of data to create a new data frame to anaylze.
corr_df = pd.DataFrame(data, columns = ['Era', 'Coefficient'])
corr_df
```

Out[56]:

	Era	Coefficient
0	early	45.96669
1	mid	58.32707
2	midlate	75.68726
3	late	54.55680
4	current	61.56485

1.3.14 Q3 Synapsis

Based on our above analysis it seems that the most improved countries on life expectancy are Kuwait, South Korea, Spain, Italy and Nicaragua.

As for the correlation between life expectancy the average income per person, there seems to be little correlation but not enough to make a stronger agrument.

Although it doesn't seem like income has a strong correlation or effect on life expectancy within countries I wonder if there are of dependent variable that have an effect. Maybe health spend?

Research Question 4: How health spend effect life expectancy?

1.3.15 Explanation

I was unlikely in the comparison between income per person and life expectancy within a country but it would be interesting to see what the correlation between health spend and life expectancy looks like. Also, the health spend is the % of total GDP which I think is a good metric because we will be looking at proportions rather than hard numbers per country.

As I'm performing many of the same functions I'm going to follow the same basic order within this question and possibly use dataframes from the past question.

```
In [57]: #Libraries and dataset:
         import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         % matplotlib inline

         health_df = pd.read_csv('total_health_spend.csv')
         life_exp_df = pd.read_csv('life_exp.csv')
```

1.3.16 Understanding Data Layout

Based on below functions around the data it is layed out identical to all other Gapminder data. We will need to remove irrelevant years, melt the data and combine reletive dataframes.

```
In [58]: #Unfortunately health spend as % of total GDP only goes from 1995 to 2010
         health_df.head()
```

```
Out[58]:        country    1995    1996    1997    1998    1999    2000    2001  \
         0  Afghanistan     nan     nan     nan     nan     nan     nan     nan
         1      Albania 0.02560 0.04040 0.04810 0.05340 0.05830 0.06350 0.06040
         2      Algeria 0.04170 0.03790 0.04060 0.04060 0.03870 0.03490 0.03840
         3      Andorra 0.07640 0.08030 0.08030 0.09850 0.07350 0.07580 0.06790
         4       Angola 0.03790 0.02170 0.02260 0.01850 0.01940 0.02410 0.03450

              2002    2003    2004    2005    2006    2007    2008    2009    2010
         0 0.05720 0.06820 0.06360 0.06630 0.06770 0.07300 0.06980 0.07580 0.07580
         1 0.06280 0.06160 0.06880 0.06840 0.06730 0.06880 0.06750 0.06880 0.06550
         2 0.03870 0.03740 0.03380 0.03060 0.03130 0.03530 0.03730 0.04580 0.04170
         3 0.07040 0.07120 0.07110 0.07220 0.07440 0.07550 0.07540 0.07520 0.07520
         4 0.02360 0.02640 0.02090 0.01960 0.02420 0.02520 0.03190 0.04950 0.02850
```

```
In [59]: #remove years for life_exp to match health spend (1996 - 2010)
         col = np.r_[1800:1996, 2011:2101]
         for i in col:
             col_drop = str(i)
             life_exp_df.drop(col_drop, axis=1, inplace=True)

         #melt the colums into rows
         health_melt_df = pd.melt(health_df, id_vars='country', var_name='year', value_name='hea
         life_exp_melt_df = pd.melt(life_exp_df, id_vars='country', var_name='year', value_name=
```

```
In [60]: #Make sure code ran successfully
         life_exp_melt_df.head()
```

```
Out[60]:        country  year  exp_years_lived
         0  Afghanistan  1996         53.80000
```

```
1      Albania  1996         74.40000
2      Algeria  1996         73.30000
3      Andorra  1996         80.00000
4       Angola  1996         50.10000
```

```
In [61]: #Double check to make sure there are 3 rows and understand more fully how to merge the
         health_melt_df.shape
```

```
Out[61]: (3040, 3)
```

```
In [62]: life_exp_melt_df.shape
```

```
Out[62]: (2805, 3)
```

```
In [63]: life_health_df = pd.merge(health_melt_df, life_exp_melt_df, on=['country', 'year'], how
         life_health_df.shape
```

```
Out[63]: (2760, 4)
```

```
In [64]: #inspect the data to further check
         life_health_df.head()
```

```
Out[64]:        country  year  health_spend  exp_years_lived
         0  Afghanistan  1996           nan         53.80000
         1      Albania  1996       0.04040         74.40000
         2      Algeria  1996       0.03790         73.30000
         3      Andorra  1996       0.08030         80.00000
         4       Angola  1996       0.02170         50.10000
```

```
In [65]: #Check for missing data
         life_health_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2760 entries, 0 to 2759
Data columns (total 4 columns):
country            2760 non-null object
year               2760 non-null object
health_spend       2731 non-null float64
exp_years_lived    2760 non-null float64
dtypes: float64(2), object(2)
memory usage: 107.8+ KB
```

We are missing some health_spend values! Next, we will have to see where the data is missing from and determine how to fix

```
In [66]: #understand data so I can clean
         life_health_df.query('health_spend == "NaN"')
```

Out[66]:

	country	year	health_spend	exp_years_lived
0	Afghanistan	1996	nan	53.80000
94	Liberia	1996	nan	48.90000
184	Afghanistan	1997	nan	53.70000
278	Liberia	1997	nan	51.90000
368	Afghanistan	1998	nan	52.80000
552	Afghanistan	1999	nan	54.40000
736	Afghanistan	2000	nan	54.60000
920	Afghanistan	2001	nan	54.80000
1252	Somalia	2002	nan	53.30000
1287	Zimbabwe	2002	nan	45.60000
1436	Somalia	2003	nan	53.70000
1471	Zimbabwe	2003	nan	45.40000
1620	Somalia	2004	nan	54.00000
1655	Zimbabwe	2004	nan	45.10000
1804	Somalia	2005	nan	54.70000
1839	Zimbabwe	2005	nan	45.10000
1988	Somalia	2006	nan	55.10000
2023	Zimbabwe	2006	nan	45.40000
2172	Somalia	2007	nan	55.00000
2207	Zimbabwe	2007	nan	45.90000
2356	Somalia	2008	nan	55.50000
2391	Zimbabwe	2008	nan	46.30000
2540	Somalia	2009	nan	55.90000
2575	Zimbabwe	2009	nan	47.20000
2648	Honduras	2010	nan	72.80000
2683	Mexico	2010	nan	75.20000
2695	Nicaragua	2010	nan	77.60000
2724	Somalia	2010	nan	55.00000
2759	Zimbabwe	2010	nan	49.70000

In [67]:
```
#Zimbabwe, Somalia and Afghanistan have to many data points missing so drop them
a = ['Zimbabwe', 'Somalia', 'Afghanistan']
for i in a:
    index_nums = life_health_df[life_health_df['country'] == i].index
    life_health_df.drop(index_nums, inplace=True)

#Check to see if worked
life_health_df.query('health_spend == "NaN"')
```

Out[67]:

	country	year	health_spend	exp_years_lived
94	Liberia	1996	nan	48.90000
278	Liberia	1997	nan	51.90000
2648	Honduras	2010	nan	72.80000
2683	Mexico	2010	nan	75.20000
2695	Nicaragua	2010	nan	77.60000

In [68]:
```
#For all other countries I'll find mean and replace the corresponding row values with s
```

```
#Find mean for all the countries health spend
liberia_mean = life_health_df.query('country == "Liberia"')['health_spend'].mean()
honduras_mean = life_health_df.query('country == "Honduras"')['health_spend'].mean()
mexico_mean = life_health_df.query('country == "Mexico"')['health_spend'].mean()
nicaragua_mean = life_health_df.query('country == "Nicaragua"')['health_spend'].mean()

#replace the NaN inputs with the mean values with the specific rows
life_health_df['health_spend'] = np.where((life_health_df['country'] == 'Liberia') & (l
life_health_df['health_spend'] = np.where((life_health_df['country'] == 'Liberia') & (l
life_health_df['health_spend'] = np.where((life_health_df['country'] == 'Honduras') & (
life_health_df['health_spend'] = np.where((life_health_df['country'] == 'Mexico') & (li
life_health_df['health_spend'] = np.where((life_health_df['country'] == 'Nicaragua') &
```

In [69]:

```
#check to make sure data is cleaned
life_health_df.info()
life_health_df.query('health_spend == 0')

#Make sure Honduras has every year listed (1996 - 2010)
life_health_df.query('country == "Honduras"')
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2715 entries, 1 to 2758
Data columns (total 4 columns):
country            2715 non-null object
year               2715 non-null object
health_spend       2715 non-null float64
exp_years_lived    2715 non-null float64
dtypes: float64(2), object(2)
memory usage: 106.1+ KB
```

Out[69]:

	country	year	health_spend	exp_years_lived
72	Honduras	1996	0.04960	69.40000
256	Honduras	1997	0.04880	69.70000
440	Honduras	1998	0.05630	63.50000
624	Honduras	1999	0.05700	70.10000
808	Honduras	2000	0.05380	70.40000
992	Honduras	2001	0.05450	70.70000
1176	Honduras	2002	0.06070	71.00000
1360	Honduras	2003	0.06400	71.20000
1544	Honduras	2004	0.06470	71.40000
1728	Honduras	2005	0.05830	71.70000
1912	Honduras	2006	0.05720	71.90000
2096	Honduras	2007	0.05910	72.20000
2280	Honduras	2008	0.06050	72.50000
2464	Honduras	2009	0.07000	72.70000
2648	Honduras	2010	0.05818	72.80000

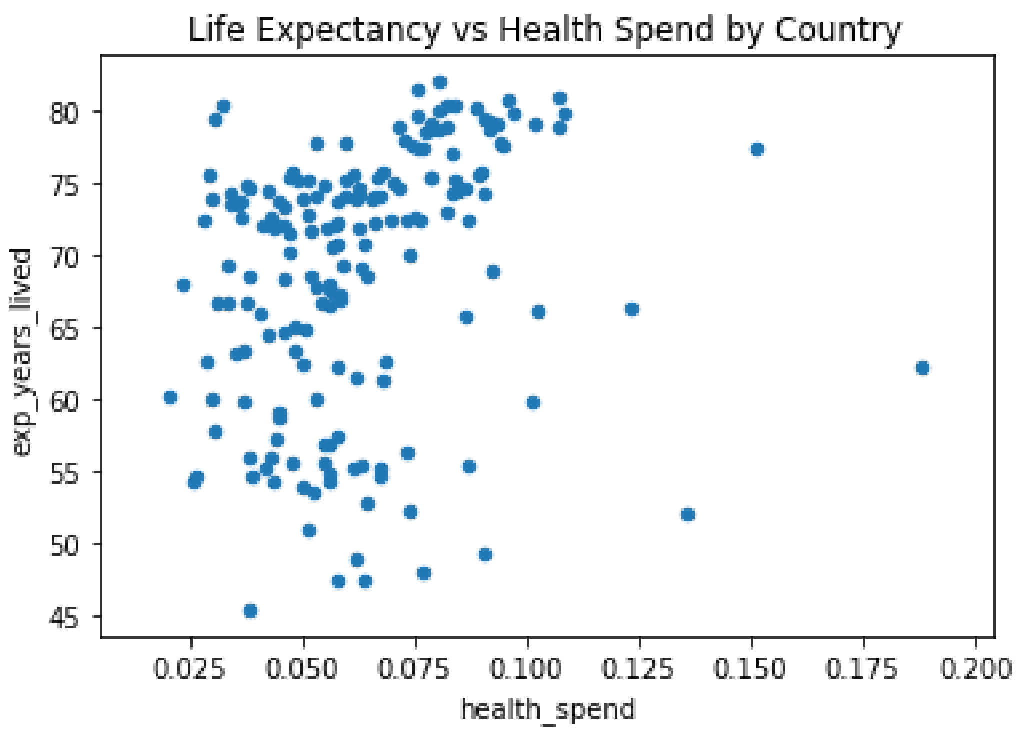
1.3.17 Analysis

For here it is very easy compared to some of our other questions. Since we are only working with a small segment of time we can going to take the average across entire time period and compare the variables in a scatter plot to better spot a correlation.

Furthermore, I will find the correlation coefficient to compare our earlier correlation of income per person to life expectancy to our new correlation using health spend.

```
In [70]: #Create scatter plot using mean values for countries
         life_health_df.groupby('country', as_index=False).mean().plot(x='health_spend', y='exp_
                                                                              title='Life Expectancy vs
```

```
Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0x7f64cf86d9b0>
```




```
In [71]: #Pearson Correlation Coefficient - higher the coefficient the more correlated the data
         column_1 = life_health_df["health_spend"]
         column_2 = life_health_df["exp_years_lived"]
         correlation = column_1.corr(column_2)
         print(correlation * 100)
```

```
24.5121296231
```

1.3.18 Q4 Synapsis

It is fair to say that there is no correlation between health spend (% of GDP) and life expectancy by country. There is only about a 24.5% correlation between the two and we can't argue for a correlation until at least after 70%.

Project Final Conclusion

> **Results:** 1. When comparing violent crimes (total murders) in proportion to countries population, Colombia, El Salvador, Guatemala, South Africa and Venezuela are the 5 countries with the highest statistical probability of violent attacks per person. 2. There is a -2.55% correlation between population density per country and total murders. Based on the data parameters, there is no correlation and population density dsoesn't effect total murders by country. 3. The top 5 most improved countries from early 1800's to post-2000 for average years lived per person are Kuwait, South Korea, Spain, Italy and Nicaragua. 4. The correlation between income per capita and life expectancy by country ranges from 45% to 75% from 1800 - 2020. As the correlations are intermittant throughout history and not substantial enough for a strong argument it's safe to say there is little to no correlation. 5. There is only a 24.5% correlation between health spend as a percentage of GDP and average life expectancy in years by country. Based on statistics, there is no correlation between budgetted health spend and life expectancy.

> **Data Limitations:** 1. We are limited to the data provided by Gapminder which does not include all countires and has no murder/population data on individual metropolitan areas which would have helped narrow down most dangerous 'place' to live. 2. Density was measured for entire area (sq km) of country which would skew that data for countries with more uninhabited land. This would be a more useful finding if it was narrowed down to cities. 3. For both total murders and health spend data files, we were limited to under 30 years of availabe data points and more limited on listed countries. Although this may be substantial enough to make a claim it would be as strong as other dataframes and results provided. 4. Global data provided by many diffing resources usually results in differing data integrity and can always be challenged and questioned.

In [ ]:
```python
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

In [ ]:

In [ ]:

In [ ]: