Investigate_a_Dataset

January 28, 2019

1 Relationship between life expenctacy, Fertility Rate and Economical growth for all countries - grouped by income level

1.1 Table of Contents

Introduction

Is there a relationship between how long people live, their number of children and the economic growth of their country? Based on datasets from Gapminder https://www.gapminder.org/data/ on all countries, the goal is to uncover if correlations exisit between those how long people live, how much babies they make and economic growth. I am working with 4 datasets: 1. income_per_person_gdppercapita_ppp_inflation_adjusted.csv the GDP or Gross Domestic Product. It has often been used to classify countries by Income. this dataset is in american dollars 2. life_expectancy_years.csv This dataset show how much people live in average in each country 3. children_per_woman_total_fertility.csv *"This entry focuses on the number of births per woman in a population. The most commonly used metric is the Total Fertility Rate (TFR) – or often simply 'fertility rate' – which measures the average number of children per woman"* https://ourworldindata.org/fertility-rate 4. gdp_total_yearly_growth.csv this dataset shows economical growth for each countries in percentage of the GDP(Gross Domestic product).

The data will be analyzed since the year 1950. the year 1950 is selected because it is after just after the 2nd world war II which has affected most countries in the west. It is also since that time that many countries all over the world could benefit from economical growth for example many asians countries. Almost all African countries gain their independance from the 1960's. And equally relevant to this analysis, with women going to work and other major change in lifestyles,the need to question traditionally big family arised in the following decades.

what is the relationship between fertility, longevity and economical growth for countries? is there even a relationship? Through the analysis that I am going to make, we will get to discover what data says about different countries from all income levels.

steps to follow:

- we are first going to Group countries by GDP or Income Level
- The datasets provided have Data from the year 1800 which is more 200 years of data. Since we are only trying to understand changes since the 1950's , we are going to reduce our data from the year 1950 to 2018.

- we will then group countries in each datasets -Fertility Rate, Life Expectancy and economic Growth based on their income level
- Compare the average life expectancy of countries based on their income level
- Compare How much children are born in country based on their income level
- Finally is there a relationship between growth, how much babies are born and economical growth in a country?

Let's begin by importing all the packages that will be needed

```
In [1]: # importing packages needed for the analysis
        import pandas as pd
        import numpy as np
        import seaborn as sns
        sns.set_style("darkgrid")
        import matplotlib.pyplot as plt
        from matplotlib.pyplot import figure
        %matplotlib inline
```

Data Wrangling
In this section I am going to load the datasets that will be used. 1.children_per_woman_total_fertility.csv 2.gdp_total_yearly_growth.csv 3.income_per_person_gdppercapita_ppp_inflation_adjusted.csv 4.life_expectancy_years.csv

These datasets are already neat and clean. In this section I will get a look at the data to prepare it for the actual analysis. The data will be loaded, checked for null values, uneccessary columns will be droped. etc..

1.1.1 General Properties

Income per person GDP This dataset will be used to group countries by income or GDP Per Capita. In order to do that, I could simply use the Quartiles in the data which simply to use group countries by the GDP income in 4 groups based on the most recent year. or to use the New Country Classification by income level from the World bank. https://blogs.worldbank.org/opendata/new-country-classifications-income-level-2018-2019. but we will get in to that later. for now let's have a quick look at the dataset

```
In [2]: #importing the income_per_person_gdppercapita_ppp_inflation_adjusted.csv file
        #running df.head() for a quick view at the data
        df_gdp = pd.read_csv('income_per_person_gdppercapita_ppp_inflation_adjusted.csv')
        df_gdp.head()
```

```
Out[2]:        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  ...
```

```
   2009   2010   2011   2012   2013   2014   2015   2016   2017   2018
0   1530   1610   1660   1840   1810   1780   1750   1740   1800   1870
1   9530   9930  10200  10400  10500  10700  11000  11400  11900  12400
2  12600  12900  13000  13200  13300  13500  13700  14000  13800  13700
3  41700  39000  42000  41900  43700  44900  46600  48200  49800  51500
4   5910   5900   5910   6000   6190   6260   6230   6030   5940   5850

[5 rows x 220 columns]
```

```
In [3]: #checking the composition of the dataframe
        df_gdp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 193 entries, 0 to 192
Columns: 220 entries, country to 2018
dtypes: int64(219), object(1)
memory usage: 331.8+ KB
```

```
In [4]: #checking the number of columns and rows
        df_gdp.shape

Out[4]: (193, 220)
```

This list is very important because we will group all the othes datasets based on income level. checking for unique values guarantees that each country is only repeated once, which is what we need to ensure that our analysis is right.

```
In [5]: #checking unique values in the GDP dataset
        unique = df_gdp.country.unique()
        len(unique)

Out[5]: 193
```

the shape of our data showed that the data has 193. we can see from the command above that all countries are only included one in the dataset. great! let's continue by checking for null values.

```
In [6]: df_gdp.isnull().values.any()

Out[6]: False
```

we can that the dataset has data on 193 countries. From the year 1800 to 2018. With no missing value. before dropping columns,let's first load the other datasets in order to understand better the data and the periods covered by all the datasets. since we will be comparing countries, it's good to know that the same countries and periods are covered.

GDP Yearly Growth This data set describre the increase in GDP by year.

In [7]:
```python
#importing the income_per_person_gdppercapita_ppp_inflation_adjusted.csv file
#running df.head() for a quick view at the data
df_growth = pd.read_csv('gdp_total_yearly_growth.csv')
df_growth.head()
```

Out[7]:
```
       country   1801   1802   1803   1804   1805   1806   1807   1808   1809  \
0  Afghanistan  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000  0.000
1      Albania  0.418  0.418  0.418  0.418  0.418  0.418  0.418  0.418  0.418
2      Algeria  0.356  0.356  0.356  0.356  0.356  0.356  0.356  0.356  0.356
3      Andorra  0.166  0.166  0.166  0.166  0.166  0.166  0.166  0.166  0.166
4       Angola  0.425  0.425  0.425  0.425  0.425  0.425  0.425  0.425  0.425

   ...   2004   2005   2006    2007   2008   2009  2010  2011   2012  2013
0  ...   6.55  12.40   4.56  13.600   2.50  20.20  8.04  6.98  14.80  4.47
1  ...   5.97   5.53   5.77   5.850   7.24   3.28  3.36  2.86   2.64  2.06
2  ...   5.41   5.38   1.72   3.420   2.02   1.70  3.57  2.31   2.58  2.99
3  ...   8.64   7.80   4.97   0.161  -4.22  -5.06 -3.43 -2.83    NaN   NaN
4  ...  11.20  20.50  18.60  23.200  13.80   2.39  3.45  3.87   4.96  3.79

[5 rows x 214 columns]
```

In [8]:
```python
df_growth.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 194 entries, 0 to 193
Columns: 214 entries, country to 2013
dtypes: float64(213), object(1)
memory usage: 324.4+ KB
```

In [9]:
```python
df_growth.shape
```

Out[9]: (194, 214)

In [10]:
```python
#checking if there is any missing values
df_growth.isnull().values.any()
```

Out[10]: True

In [11]:
```python
#checking how many null values are in the dataframe. depending on the volumes of missin
df_growth.isnull().sum().sum()
```

Out[11]: 42

In [12]:
```python
nan_rows = df_growth.isnull().any().any()
nan_rows
```

Out[12]: True

The growth by GDP Dataset had 194 entries or countries. with 214 columns. As we can see from the df_growth.info() command, the period covered goes from 1801 to 2013. he previous dataset on gdp/income had had a shape of (193,220). This dataset has a shape of (194,214). Since our exploration will be a comparaison, after we load all the dataset, we need to make sure that the countries and periods covered are the same. or at least understand and notice the irregularities and includes them in our conclusions.

1.1.2 Life Expectancy

This data set describre the average life expectancy in years. we are going to import the file (life_expectancy_years.csv)

```
In [13]: # importing the dataset
         #checking the head
         df_expectancy = pd.read_csv('life_expectancy_years.csv')
         df_expectancy.head()

Out[13]:        country  1800  1801  1802  1803  1804  1805  1806  1807  1808  ...   \
         0  Afghanistan  28.2  28.2  28.2  28.2  28.2  28.2  28.1  28.1  28.1  ...
         1      Albania  35.4  35.4  35.4  35.4  35.4  35.4  35.4  35.4  35.4  ...
         2      Algeria  28.8  28.8  28.8  28.8  28.8  28.8  28.8  28.8  28.8  ...
         3      Andorra   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN  ...
         4       Angola  27.0  27.0  27.0  27.0  27.0  27.0  27.0  27.0  27.0  ...

            2009  2010  2011  2012  2013  2014  2015  2016  2017  2018
         0  55.7  56.2  56.7  57.2  57.7  57.8  57.9  58.0  58.4  58.7
         1  75.9  76.3  76.7  77.0  77.2  77.4  77.6  77.7  77.9  78.0
         2  76.3  76.5  76.7  76.8  77.0  77.1  77.3  77.4  77.6  77.9
         3  82.7  82.7  82.6  82.6  82.6  82.6  82.5  82.5   NaN   NaN
         4  59.3  60.1  60.9  61.7  62.5  63.3  64.0  64.7  64.9  65.2

         [5 rows x 220 columns]

In [14]: #checking the shape of the dataframe
         df_expectancy.shape

Out[14]: (187, 220)

In [15]: #the dataframe has 220 columns, and 187 rows. datatypes are float which is quite normal
         df_expectancy.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 187 entries, 0 to 186
Columns: 220 entries, country to 2018
dtypes: float64(219), object(1)
memory usage: 321.5+ KB


In [16]: #Checking if there is any null values
         df_expectancy.isnull().values.any()
```

Out[16]: True

In [17]: df_expectancy.isnull().sum().head()

```
Out[17]: country    0
         1800       3
         1801       3
         1802       3
         1803       3
         dtype: int64
```

In [18]: #counting null values

```
df_expectancy.isnull().sum().sum()
```

Out[18]: 516

516 seems to be too big of a number to just drop everything. this dataframe covers period from 1800 to 2018. In order to respond to our analysis questions we will only need the period from 1950. we will come back to this later. now let's load the fertility dataset. The null values will be handled once the data is grouped.

1.1.3 Fertility Rate or Number of children per woman

This data set describre the average number of children per woman in all countries. we are going to import the file (children_per_woman_total_fertility.csv)

In [19]:

```
#import the children_per_woman_total_fertility.csv dataset
df_birth = pd.read_csv('children_per_woman_total_fertility.csv')
df_birth.head()
```

Out[19]:

```
               country  1800  1801  1802  1803  1804  1805  1806  1807  1808  \
0          Afghanistan  7.00  7.00  7.00  7.00  7.00  7.00  7.00  7.00  7.00
1              Albania  4.60  4.60  4.60  4.60  4.60  4.60  4.60  4.60  4.60
2              Algeria  6.99  6.99  6.99  6.99  6.99  6.99  6.99  6.99  6.99
3               Angola  6.93  6.93  6.93  6.93  6.93  6.93  6.93  6.94  6.94
4  Antigua and Barbuda  5.00  5.00  4.99  4.99  4.99  4.98  4.98  4.97  4.97

   ...  2009  2010  2011  2012  2013  2014  2015  2016  2017  2018
0  ...  6.04  5.82  5.60  5.38  5.17  4.98  4.80  4.64  4.48  4.33
1  ...  1.65  1.65  1.67  1.69  1.70  1.71  1.71  1.71  1.71  1.71
2  ...  2.83  2.89  2.93  2.94  2.92  2.89  2.84  2.78  2.71  2.64
3  ...  6.24  6.16  6.08  6.00  5.92  5.84  5.77  5.69  5.62  5.55
4  ...  2.15  2.13  2.12  2.10  2.09  2.08  2.06  2.05  2.04  2.03

[5 rows x 220 columns]
```

In [20]:

```
#checking the dataframe
df_birth.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 184 entries, 0 to 183
Columns: 220 entries, country to 2018
dtypes: float64(219), object(1)
memory usage: 316.3+ KB
```

```
In [21]: #checking the shape of the dataframe
         df_birth.shape

Out[21]: (184, 220)

In [22]: # checking null values
         df_birth.isnull().values.any()

Out[22]: False
```

There are no missing values in the Fertility Rate Dataset. the dataset covers from the year 1800 to the year 2018. The shape of the dataframe is 184 rows and 220 columns.

2 Grouping by GDP Levels

In this section we are going to check if the same countries are present in all 4 datasets, check the period covered, group by income levels. after this step we will proceed with the Exploratoy Data Analysis.

group the countries by income level (4 levels)

create a new daframe for each of those levels that will be used for Exploratory Data Analysis later

check the countries in the dataframe

Adjust the periods covered by all 4 datasets

Comparings Datasets shapes By comparing the 4 datasets shapes we can see that the number of columns is not the same in all 4 datasets. The columns represents the years. the rows the countries included.As you can see in the table below. But for now let's focus on grouping the countries by Income Level based on the GDP Dataset.

Dataset shape	Gdp_Income_Level	Life Expectancy	Fertility Rate	Gdp Growth
columns	193	187	184	194
rows	220	220	220	214

let's make sure that the countries compared are the same, we are going to compare the columns from all the 4 datasets. we will look into that later. let's proceed with the grouping by income first. since the grouping of the other dataset will also be done based on gdp.

2.0.1 Grouping by Income Level

the file income_per_person_gdppercapita_ppp_inflation_adjusted.csv from Gapminder gives data from 1800 to 2018. since we are trying to group and observe what happened in the last decades, we are going to use the latest year to group countries. we are going to group countries based on their 2018 GDP.

```
In [23]: #2018 is the latest year
         df_gdp.head(1)
```

```
Out[23]:        country  1800  1801  1802  1803  1804  1805  1806  1807  1808  ...   \
         0  Afghanistan   603   603   603   603   603   603   603   603   603  ...

            2009  2010  2011  2012  2013  2014  2015  2016  2017  2018
         0  1530  1610  1660  1840  1810  1780  1750  1740  1800  1870

         [1 rows x 220 columns]
```

```
In [24]: #Trying to understand the distribution of the gdp per capita based on the Quartiles.
         df_gdp['2018'].describe()
```

```
Out[24]: count       193.000000
         mean      18241.502591
         std       19664.365483
         min         629.000000
         25%        3670.000000
         50%       12100.000000
         75%       25500.000000
         max      121000.000000
         Name: 2018, dtype: float64
```

if we consider the number below, the 25% of low income countries have 3670 Dollars and below the second group in the 50 would have a GDP of 12100 per capita and below, the third group 25500 Dollars of GDP per Capita the last and richest group would have 121000 Dollars of GDP per capita.

Below we added an image from the world bank Group whith the most recent classification of countries based on income level. the classification is from 2018, this year. So I think its might be a more realistic categorisation of countries by income level. After some time looking for officials classifications of countries by Income Level, its seemed like the world bank would be a more credible authority. The Value below are the GNI or Gross National Income. they are not exactly the GDP but might be a more realistic way to compare countries than Quartiles.

https://blogs.worldbank.org/opendata/new-country-classifications-income-level-2018-2019#comments

We will use the classification above to continue our analysis

Low Income Countries countries with less than 995 USD in GDP per capita

```
In [25]: # grouping countries by income using loc and only keeping the country column
         low_income = df_gdp.loc[df_gdp['2018'] < 995, ['country', '2018']]
         low_income
```

```
Out[25]:                        country  2018
        27                       Burundi   691
        32      Central African Republic   689
        38              Congo, Dem. Rep.   751
        94                       Liberia   801
        123                        Niger   949
        154                      Somalia   629
```

Lower Middle Income Countries countries with GDP per capita between 996 and 3895 USD

```
In [26]: # grouping countries by income using loc and only keeping the country column
         lower_middle_income = df_gdp.loc[(df_gdp['2018'] > 995) & (df_gdp['2018'] < 3896), ['co
         lower_middle_income.head()
```

```
Out[26]:          country  2018
        0     Afghanistan  1870
        13     Bangladesh  3720
        18          Benin  2170
        26   Burkina Faso  1710
        28       Cambodia  3830
```

Upper Middle Income Countries countries with GDP between 3896 and 12055 USD

```
In [27]: # grouping countries by income using loc and only keeping the country column
         upper_middle_income = df_gdp.loc[(df_gdp['2018'] >= 3896) & (df_gdp['2018'] <= 12055),
         upper_middle_income.head()
```

```
Out[27]:      country  2018
        4     Angola  5850
        7    Armenia  8660
        17    Belize  7710
        19    Bhutan  9930
        20   Bolivia  6980
```

High Income Countries Countries with GDP Per capita which is above 12055 USD

```
In [28]: # grouping countries by income using loc and only keeping the country column
         high_income = df_gdp.loc[df_gdp['2018'] > 12055, ['country', '2018']]
         high_income.head()
```

```
Out[28]:                country   2018
        1              Albania  12400
        2              Algeria  13700
        3              Andorra  51500
        5  Antigua and Barbuda  21000
        6            Argentina  18900
```

Verifying that the count all the countries included in the income file found a group

```
In [29]: #veryfing that the count of our 4 new dataframes are equals to the total of gdp_df they
         #The number match our original GDP file
         low_income.count()+ lower_middle_income.count() + upper_middle_income.count() + high_in

Out[29]: country    193
         2018       193
         dtype: int64
```

the count match our originial GDP file. meaning that each country is grouped. perfect! we are now going to group countries in the life expectancy dataset in the income level group as set above.

2.0.2 Life Expectancy Grouping by Income Level, from the year 1950

Now we are going to group the other datasets by Income. let's start by the life expectancy Dataset based on the classification by countries's income, we are equally going to classify the other datasets in 4 groups. we are going to create 4 groups within the life expectancy group: * low_income_expectancy * lower_middle_income_expectancy * upper_middle_income_expectancy * high_income_expectancy

Limiting the dataset from the year 1950 this dataset has data from the year 1800. lets remove the 150 years that are not necessary to answer our questions and only keep the decades that are of interest to us. But that still leaves us with 68 years of data or meaning 68 rows per country. In order to properly understand the progress, we are going to divide the data in decades from 1950 to 2018. Since we want to globally understand the tendancy, randomly picking a point in time every decade should give an idea of the general tendancy.

```
In [30]: #dropping irrelevant columns.  from the year 1800 to 1949
         cols=  df_expectancy.columns[1:151]
         df_expectancy.drop(cols,axis=1, inplace=True)
         df_expectancy.head()

Out[30]:        country  1950  1951  1952  1953  1954  1955  1956  1957  1958  ...   \
         0  Afghanistan  32.0  32.4  33.0  33.7  34.4  35.1  35.8  36.5  37.2  ...
         1      Albania  54.5  54.7  55.2  55.8  56.5  57.3  58.3  59.3  60.4  ...
         2      Algeria  46.9  47.1  47.6  48.1  48.6  49.2  49.7  50.3  50.9  ...
         3      Andorra   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN   NaN  ...
         4       Angola  36.6  36.9  37.5  38.1  38.7  39.3  39.9  40.5  41.2  ...

            2009  2010  2011  2012  2013  2014  2015  2016  2017  2018
         0  55.7  56.2  56.7  57.2  57.7  57.8  57.9  58.0  58.4  58.7
         1  75.9  76.3  76.7  77.0  77.2  77.4  77.6  77.7  77.9  78.0
         2  76.3  76.5  76.7  76.8  77.0  77.1  77.3  77.4  77.6  77.9
         3  82.7  82.7  82.6  82.6  82.6  82.6  82.5  82.5   NaN   NaN
         4  59.3  60.1  60.9  61.7  62.5  63.3  64.0  64.7  64.9  65.2

         [5 rows x 70 columns]
```

the dataset above would still be too much unnecessary data. so we are only to randomly select one year every decade from 1950.

```
In [31]: #selecting the years 1950, 1960, 1970, 1980, 1990, 2000, 2010, 2018
         df_expectancy = df_expectancy[['country','1950', '1960', '1970', '1980', '1990', '2000'
         df_expectancy.head()
```

Out[31]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
0	Afghanistan	32.0	38.6	45.8	43.3	51.6	51.6	56.2	58.7
1	Albania	54.5	62.7	67.4	72.3	73.9	74.4	76.3	78.0
2	Algeria	46.9	52.0	57.5	62.1	71.0	73.9	76.5	77.9
3	Andorra	NaN	NaN	76.0	78.7	79.5	81.8	82.7	NaN
4	Angola	36.6	42.4	48.7	49.9	50.2	53.4	60.1	65.2

Life Expectancy grouping For Low Income Income Countries we are going to use the isin to group countries which are in low income country dataframe created earlier

```
In [32]: #grouping life for low income countries
         low_income_expectancy = df_expectancy.loc[df_expectancy.country.isin(low_income.country
         low_income_expectancy.head(1)
```

Out[32]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
27	Burundi	39.0	42.0	44.7	46.3	48.0	47.9	57.7	61.1

Life Expectancy grouping For Lower Middle Income Countries Grouping Lower Middle Income Countries Life Expectancy

```
In [33]: #grouping life for lower middle income countries
         lower_middle_income_expectancy = df_expectancy.loc[df_expectancy.country.isin(lower_mid
         lower_middle_income_expectancy.head(1)
```

Out[33]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
0	Afghanistan	32.0	38.6	45.8	43.3	51.6	51.6	56.2	58.7

Life Expectancy grouping For Upper Middle Income Countries Grouping Life Expectancy data for Upper Middle Income Countries

```
In [34]: #grouping life for upper middle income countries
         upper_middle_income_expectancy = df_expectancy.loc[df_expectancy.country.isin(upper_mid
         upper_middle_income_expectancy.head(1)
```

Out[34]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
4	Angola	36.6	42.4	48.7	49.9	50.2	53.4	60.1	65.2

Life Expectancy grouping For High Income Countries Grouping Life Expectancy Data for High Income Countries

```
In [35]: #grouping life for High income countries
         high_income_expectancy = df_expectancy.loc[df_expectancy.country.isin(high_income.count
         high_income_expectancy.head(1)
```

Out[35]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
1	Albania	54.5	62.7	67.4	72.3	73.9	74.4	76.3	78.0

2.0.3 Fertility Rate Grouping by Income Level, from the year 1950

based on the classification by countries's income, we are equally going to classify this dataset in 4 groups. we are going to create 4 groups within the life expectancy group: * low_income_birth * lower_middle_income_birth * upper_middle_income_birth * high_income_birth

Limiting the dataset from the year 1950 this dataset has data from the year 1800. lets remove the 150 years that are not necessary to answer our questions and only keep the decades that are of interest to us.

```
In [36]: cols=  df_birth.columns[1:151]
         df_birth.drop(cols,axis=1, inplace=True)
         df_birth.head()
```

```
Out[36]:                country  1950  1951  1952  1953  1954  1955  1956  1957  1958  \
         0          Afghanistan  7.57  7.56  7.55  7.54  7.53  7.52  7.51  7.49  7.48
         1              Albania  5.87  5.97  6.13  6.27  6.37  6.45  6.50  6.53  6.54
         2              Algeria  7.49  7.47  7.44  7.43  7.41  7.41  7.41  7.43  7.45
         3               Angola  7.11  7.13  7.15  7.17  7.20  7.23  7.27  7.31  7.36
         4  Antigua and Barbuda  4.45  4.46  4.50  4.52  4.53  4.53  4.53  4.51  4.49

            ...   2009  2010  2011  2012  2013  2014  2015  2016  2017  2018
         0  ...   6.04  5.82  5.60  5.38  5.17  4.98  4.80  4.64  4.48  4.33
         1  ...   1.65  1.65  1.67  1.69  1.70  1.71  1.71  1.71  1.71  1.71
         2  ...   2.83  2.89  2.93  2.94  2.92  2.89  2.84  2.78  2.71  2.64
         3  ...   6.24  6.16  6.08  6.00  5.92  5.84  5.77  5.69  5.62  5.55
         4  ...   2.15  2.13  2.12  2.10  2.09  2.08  2.06  2.05  2.04  2.03

         [5 rows x 70 columns]
```

```
In [37]: #selecting the years 1950, 1960, 1970, 1980, 1990, 2000, 2010, 2018
         df_birth = df_birth[['country','1950', '1960', '1970', '1980', '1990', '2000', '2010',
         df_birth.head()
```

```
Out[37]:                country  1950  1960  1970  1980  1990  2000  2010  2018
         0          Afghanistan  7.57  7.45  7.45  7.45  7.47  7.49  5.82  4.33
         1              Albania  5.87  6.49  4.91  3.62  2.98  2.16  1.65  1.71
         2              Algeria  7.49  7.52  7.64  6.79  4.73  2.51  2.89  2.64
         3               Angola  7.11  7.48  7.60  7.50  7.25  6.64  6.16  5.55
         4  Antigua and Barbuda  4.45  4.43  3.68  2.12  2.06  2.32  2.13  2.03
```

Fertility grouping For Low Income Countries

```
In [38]: # grouping the data for low income country
         low_income_birth = df_birth.loc[df_birth.country.isin(low_income.country.tolist())]
         low_income_birth.head(1)
```

```
Out[38]:     country  1950  1960  1970  1980  1990  2000  2010  2018
         26  Burundi  6.82  6.95  7.29  7.42  7.51  7.01  6.26  5.53
```

Fertily grouping For Lower Middle Income Countries

```
In [39]: # grouping the data for lower middle income country
         lower_middle_income_birth = df_birth.loc[df_birth.country.isin(lower_middle_income.coun
         lower_middle_income_birth.head(1)
```

Out[39]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
0	Afghanistan	7.57	7.45	7.45	7.45	7.47	7.49	5.82	4.33

Fertily grouping For Upper Middle Income Countries

```
In [40]: # grouping the data for lower middle income country
         upper_middle_income_birth = df_birth.loc[df_birth.country.isin(upper_middle_income.coun
         upper_middle_income_birth.head(1)
```

Out[40]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
3	Angola	7.11	7.48	7.6	7.5	7.25	6.64	6.16	5.55

Fertily grouping For High Income Countries

```
In [41]: # grouping the data for High income country
         high_income_birth = df_birth.loc[df_birth.country.isin(high_income.country.tolist())]
         high_income_birth.head(1)
```

Out[41]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
1	Albania	5.87	6.49	4.91	3.62	2.98	2.16	1.65	1.71

2.0.4 Economic Growth Grouping by Income Level, from the year 1950

based on the classification by countries's income, we are equally going to classify this dataset in 4 groups. we are going to create 4 groups within the Economic Growth Dataset: * low_income_growth * lower_middle_income_growth * upper_middle_income_growth * high_income_growth

Limiting the dataset from the year 1950 this dataset has data from the year 1801. lets remove the 149 years that are not necessary to answer our questions and only keep the decades that are of interest to us.

```
In [42]: cols=  df_growth.columns[1:150]
         df_growth.drop(cols,axis=1, inplace=True)
         df_growth.head()
```

Out[42]:

	country	1950	1951	1952	1953	1954	1955	1956	1957 \
0	Afghanistan	1.42	2.800	3.26	5.97	1.97	1.83	4.32	-0.182
1	Albania	0.87	6.460	2.53	6.77	5.84	8.52	4.11	9.760
2	Algeria	1.70	0.955	4.29	1.50	7.12	2.68	9.78	11.400
3	Andorra	4.48	12.100	12.40	12.50	12.50	12.40	12.20	12.000
4	Angola	4.04	4.090	4.19	4.13	-2.31	8.38	-1.59	9.790

```
    1958  ...   2004   2005   2006    2007   2008   2009  2010  2011   2012  \
0   5.42  ...   6.55  12.40   4.56  13.600   2.50  20.20  8.04  6.98  14.80
1   7.83  ...   5.97   5.53   5.77   5.850   7.24   3.28  3.36  2.86   2.64
2   3.74  ...   5.41   5.38   1.72   3.420   2.02   1.70  3.57  2.31   2.58
3  11.80  ...   8.64   7.80   4.97   0.161  -4.22  -5.06 -3.43 -2.83    NaN
4   5.46  ...  11.20  20.50  18.60  23.200  13.80   2.39  3.45  3.87   4.96

   2013
0  4.47
1  2.06
2  2.99
3   NaN
4  3.79

[5 rows x 65 columns]
```

In [43]:
```python
#selecting the years 1950, 1960, 1970, 1980, 1990, 2000, 2010, 2018
df_growth = df_growth[['country', '1950', '1960' , '1970','1980', '1990', '2000', '2010
df_growth.head()
```

Out[43]:
```
       country  1950   1960   1970  1980   1990  2000  2010  2013
0  Afghanistan  1.42   3.37   1.94 -0.28 -0.885  1.74  8.04  4.47
1      Albania  0.87   8.40   6.33  2.81  1.940  6.76  3.36  2.06
2      Algeria  1.70   6.87  10.10  2.02 -1.450  2.45  3.57  2.99
3      Andorra  4.48  11.40   9.36  2.21  3.830  1.42 -3.43   NaN
4       Angola  4.04   4.09   6.50  2.73 -0.445  3.01  3.45  3.79
```

GDP Growth grouping For Low Income Countries

In [44]:
```python
# grouping the data for low income countries
low_income_growth = df_growth.loc[df_growth.country.isin(low_income.country.tolist())]
low_income_growth.head(1)
```

Out[44]:
```
    country   1950  1960  1970  1980  1990  2000  2010  2013
27  Burundi  0.855  1.47  26.3   6.4  3.63 -1.15  3.98  3.91
```

GDP Growth grouping For Lower middle Income Countries

In [45]:
```python
# grouping the data for lower middle income countries
lower_middle_income_growth = df_growth.loc[df_growth.country.isin(lower_middle_income.c
lower_middle_income_growth.head(1)
```

Out[45]:
```
       country  1950  1960  1970  1980   1990  2000  2010  2013
0  Afghanistan  1.42  3.37  1.94 -0.28 -0.885  1.74  8.04  4.47
```

GDP Growth grouping For Upper middle Income Countries

In [46]:
```python
# grouping the data for upper middle income countries
upper_middle_income_growth = df_growth.loc[df_growth.country.isin(upper_middle_income.c
upper_middle_income_growth.head(1)
```

Out[46]:
```
   country  1950  1960  1970  1980   1990  2000  2010  2013
4   Angola  4.04  4.09   6.5  2.73 -0.445  3.01  3.45  3.79
```

GDP Growth grouping For High Income Countries

In [47]:
```
# grouping the data for upper middle income countries
high_income_growth = df_growth.loc[df_growth.country.isin(high_income.country.tolist())
high_income_growth.head(1)
```

Out[47]:
```
    country  1950  1960  1970  1980  1990  2000  2010  2013
1   Albania  0.87   8.4  6.33  2.81  1.94  6.76  3.36  2.06
```

Exploratory Data Analysis
so Now we have grouped all the countries in 4 categories based on income level. From now on we are going to compare Low income countries, lower middle income countries, upper middle income countries and high income countries on 3 metrics: Life expectancy, Fertility Rate and Economical Growth since the 1950's.

Since the data is already cleaned and grouped, we are going to plot all the different metrics to have a visual representation of what is going on in each group for each metric

2.0.5 comparaison on Life Expectancy: How much does the Income Level of a country influence the life expectancy of its habitants? Compared to countries from different income Level

- low_income_expectancy
- lower_middle_income_expectancy
- upper_middle_income_expectancy
- high_income_expectancy

Life Expectancy In Countries with Low Income (Less than 995 USD of GNI per Capita in 2018)
In order to analyze the data we need to put first change its format from wide shape to long range. we will then calculate the mean life expectancy

In [48]:
```
#setting the country column as the index
low_income_expectancy.set_index('country', inplace=True)
low_income_expectancy
```

Out[48]:

country	1950	1960	1970	1980	1990	2000	2010	2018
Burundi	39.0	42.0	44.7	46.3	48.0	47.9	57.7	61.1
Central African Republic	36.5	41.4	48.3	49.6	48.2	44.5	47.5	51.6
Congo, Dem. Rep.	42.8	46.5	50.3	52.6	53.8	53.4	57.5	62.4
Liberia	38.2	41.3	47.5	51.5	49.9	54.5	60.8	65.4
Niger	40.5	42.0	43.6	43.9	47.1	52.2	58.8	62.5
Somalia	38.9	44.2	49.8	50.8	50.7	52.1	53.1	58.0

Verifying if there is any null values in the dataframe. checking and handling null values now (if any) because now I can use the mean value of the given group to fill in the missing values. The mean value of the same group might a more realistic value than the mean off all group combined. we are going to apply the same method for all groups.

In [49]:
```
#verifying if there is null values. there is none
low_income_expectancy.isnull().sum().sum()
```

Out[49]: 0

In [50]:
```
low_income_expectancy.describe()
```

Out[50]:

```
            1950      1960       1970       1980       1990       2000  \
count   6.000000   6.00000   6.000000   6.000000   6.000000   6.000000
mean   39.316667  42.90000  47.366667  49.116667  49.616667  50.766667
std     2.144217   2.05329   2.709736   3.347487   2.437553   3.799825
min    36.500000  41.30000  43.600000  43.900000  47.100000  44.500000
25%    38.375000  41.55000  45.400000  47.125000  48.050000  48.950000
50%    38.950000  42.00000  47.900000  50.200000  49.050000  52.150000
75%    40.125000  43.65000  49.425000  51.325000  50.500000  53.100000
max    42.800000  46.50000  50.300000  52.600000  53.800000  54.500000

            2010       2018
count   6.000000   6.000000
mean   55.900000  60.166667
std     4.829493   4.832667
min    47.500000  51.600000
25%    54.200000  58.775000
50%    57.600000  61.750000
75%    58.525000  62.475000
max    60.800000  65.400000
```

we can see the mean age for this group. in 1950 it was 39.31 years, 42.9 years 10 years later in 1960. it went up to 60 years in 2018. below we will plot this to more easily understand the evolution in this group.

we can also see that the life expectancy for this group went from less than 40 years in 1950 to 60 years in 2018. there was a clear and consistent increase in life expectancy. Now lets continue with the Lower Middle Income Countries. We will go through the same steps. first shapping the data. and then plotting the mean of the two groups so that a comparaison can be made.

Life Expectancy In Countries with Lower Middle Income (Countries with GNI per Capita between 996 and 3895 USD)

In [51]:
```
#checking if the dataframe looks ok
lower_middle_income_expectancy.head(1)
```

Out[51]:

```
       country  1950  1960  1970  1980  1990  2000  2010  2018
0  Afghanistan  32.0  38.6  45.8  43.3  51.6  51.6  56.2  58.7
```

In [52]:
```
lower_middle_income_expectancy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 47 entries, 0 to 186
Data columns (total 9 columns):
```

```
country    47 non-null object
1950       46 non-null float64
1960       46 non-null float64
1970       47 non-null float64
1980       47 non-null float64
1990       47 non-null float64
2000       47 non-null float64
2010       47 non-null float64
2018       46 non-null float64
dtypes: float64(8), object(1)
memory usage: 3.7+ KB
```

we can see that they some missing values. let's look more in to that.

In [53]:
```
#checking if there is any missing values
lower_middle_income_expectancy.isnull().sum()
```

Out[53]:
```
country    0
1950       1
1960       1
1970       0
1980       0
1990       0
2000       0
2010       0
2018       1
dtype: int64
```

There 3 missing values. one in 1950 and one in 1960 and a last one in 2018. we are going to replace those missing values by the mean value of each column

In [54]:
```
# replacing missing values with means of each columns
#cheking if there any missing values left
lower_middle_income_expectancy['1950'].fillna((lower_middle_income_expectancy['1950'].m
lower_middle_income_expectancy['1960'].fillna((lower_middle_income_expectancy['1960'].m
lower_middle_income_expectancy['2018'].fillna((lower_middle_income_expectancy['2018'].m
lower_middle_income_expectancy.isnull().sum()
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/generic.py:3660: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self._update_inplace(new_data)
```

Out[54]:
```
country    0
1950       0
1960       0
```

```
1970      0
1980      0
1990      0
2000      0
2010      0
2018      0
dtype: int64
```

```
In [55]: #checking general statistics about countries in the lower middle income group
         lower_middle_income_expectancy.describe()
```

```
Out[55]:             1950       1960       1970       1980       1990       2000  \
         count  47.000000  47.000000  47.000000  47.000000  47.000000  47.000000
         mean   40.543478  45.747826  51.385106  55.151064  57.293617  57.600000
         std     6.083072   6.060124   6.689706   6.643855   6.140224   6.747334
         min    23.800000  33.000000  39.800000  43.300000  46.600000  44.100000
         25%    35.950000  41.550000  45.600000  50.100000  52.150000  52.250000
         50%    40.400000  44.800000  51.000000  54.900000  57.500000  57.600000
         75%    44.750000  50.350000  56.050000  59.650000  61.350000  63.300000
         max    52.500000  57.300000  67.400000  70.800000  71.600000  73.300000

                    2010       2018
         count  47.000000  47.000000
         mean   61.180851  65.041304
         std     7.620500   4.710238
         min    32.100000  51.100000
         25%    57.050000  61.200000
         50%    61.700000  64.600000
         75%    66.000000  68.150000
         max    76.200000  73.400000
```

By having a quick look at the data returned above, we can see that the mean age is in general higher than in the Lower middle income countries than it is in the Low income Countries. In 1950 the mean life expectancy in this group was 40 and in 2018 it is 65 years old. Against about 39 and 60 years in the low income group.

we can see that the life expectancy is consistently higher in the lower middle income countries (cyan line) if we compare to lower income countries (red line). let's continue our camparison by adding Upper Middle Income Countries to the next plot.

Life Expectancy in Upper Middle Income Countries (GNI Per capita between 3896 and 12,055 USD)

```
In [56]: #checking the shape of this dataframe
         upper_middle_income_expectancy.head(1)
```

```
Out[56]:   country  1950  1960  1970  1980  1990  2000  2010  2018
         4  Angola  36.6  42.4  48.7  49.9  50.2  53.4  60.1  65.2
```

```
In [57]: #checking for missing values
         upper_middle_income_expectancy.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 41 entries, 4 to 183
Data columns (total 9 columns):
country    41 non-null object
1950       40 non-null float64
1960       40 non-null float64
1970       41 non-null float64
1980       41 non-null float64
1990       41 non-null float64
2000       41 non-null float64
2010       41 non-null float64
2018       40 non-null float64
dtypes: float64(8), object(1)
memory usage: 3.2+ KB
```

In [58]:
```
upper_middle_income_expectancy.isnull().sum()
```

Out[58]:
```
country    0
1950       1
1960       1
1970       0
1980       0
1990       0
2000       0
2010       0
2018       1
dtype: int64
```

In [59]:
```
# replacing missing values with means of each columns
#cheking if there any missing values left
upper_middle_income_expectancy['1950'].fillna((upper_middle_income_expectancy['1950'].m
upper_middle_income_expectancy['1960'].fillna((upper_middle_income_expectancy['1960'].m
upper_middle_income_expectancy['2018'].fillna((upper_middle_income_expectancy['2018'].m
upper_middle_income_expectancy.isnull().sum()
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/generic.py:3660: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self._update_inplace(new_data)
```

Out[59]:
```
country    0
1950       0
1960       0
1970       0
1980       0
1990       0
```

```
2000       0
2010       0
2018       0
dtype: int64
```

In [60]:
```
#checking generals statistic for this group
upper_middle_income_expectancy.describe()
```

Out[60]:
```
            1950       1960       1970       1980       1990       2000  \
count  41.000000  41.000000  41.000000  41.000000  41.000000  41.000000
mean   47.455000  53.070000  58.224390  62.631707  65.595122  66.687805
std     8.388443   7.654548   7.112376   6.399900   6.171060   6.942521
min    31.900000  39.700000  42.200000  47.900000  50.200000  47.500000
25%    42.100000  47.000000  51.500000  57.700000  61.500000  62.600000
50%    46.000000  53.070000  58.300000  64.800000  67.200000  68.600000
75%    55.200000  59.500000  64.500000  67.500000  70.200000  71.700000
max    65.800000  69.400000  69.500000  73.100000  74.600000  75.600000

            2010       2018
count  41.000000  41.000000
mean   69.285366  71.652500
std     6.050147   4.364286
min    47.000000  58.600000
25%    66.200000  68.800000
50%    71.300000  72.400000
75%    73.100000  74.800000
max    77.400000  78.700000
```

By Only looking at the mean value for each year we can see that this group has higher life expectancy than previous groups.

Life Expectancy in High Income Countries (GNI Per capita > 12,055 USD)

In [61]:
```
high_income_expectancy.head(1)
```

Out[61]:
```
   country  1950  1960  1970  1980  1990  2000  2010  2018
1  Albania  54.5  62.7  67.4  72.3  73.9  74.4  76.3  78.0
```

In [62]:
```
#checking for null values
high_income_expectancy.isnull().sum()
```

Out[62]:
```
country    0
1950       1
1960       1
1970       0
1980       0
1990       0
2000       0
2010       0
2018       1
dtype: int64
```

```
In [63]: # replacing missing values with means of each columns
         #cheking if there any missing values left
         high_income_expectancy['1950'].fillna((high_income_expectancy['1950'].mean()), inplace=
         high_income_expectancy['1960'].fillna((high_income_expectancy['1960'].mean()), inplace=
         high_income_expectancy['2018'].fillna((high_income_expectancy['2018'].mean()), inplace=
         high_income_expectancy.isnull().sum().sum()
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/generic.py:3660: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self._update_inplace(new_data)
```

```
Out[63]: 0
```

```
In [64]: high_income_expectancy.describe()
```

Out[64]:

	1950	1960	1970	1980	1990	2000	2010	2018
count	93.000000	93.000000	93.000000	93.000000	93.000000	93.000000	93.000000	93.000000
mean	56.678261	62.081522	66.296774	69.516129	72.023656	73.575269	76.135484	77.718478
std	9.592001	9.078521	6.711079	5.573780	4.643331	5.796225	5.339998	4.331255
min	29.700000	30.900000	39.100000	48.200000	48.200000	46.700000	54.300000	63.500000
25%	51.600000	57.700000	64.600000	67.500000	70.000000	71.700000	74.400000	75.700000
50%	58.400000	63.700000	68.000000	70.500000	72.100000	74.500000	76.500000	77.900000
75%	64.000000	69.100000	70.900000	73.200000	75.300000	77.500000	80.100000	81.300000
max	71.600000	74.200000	76.000000	78.700000	79.500000	81.800000	82.800000	84.200000

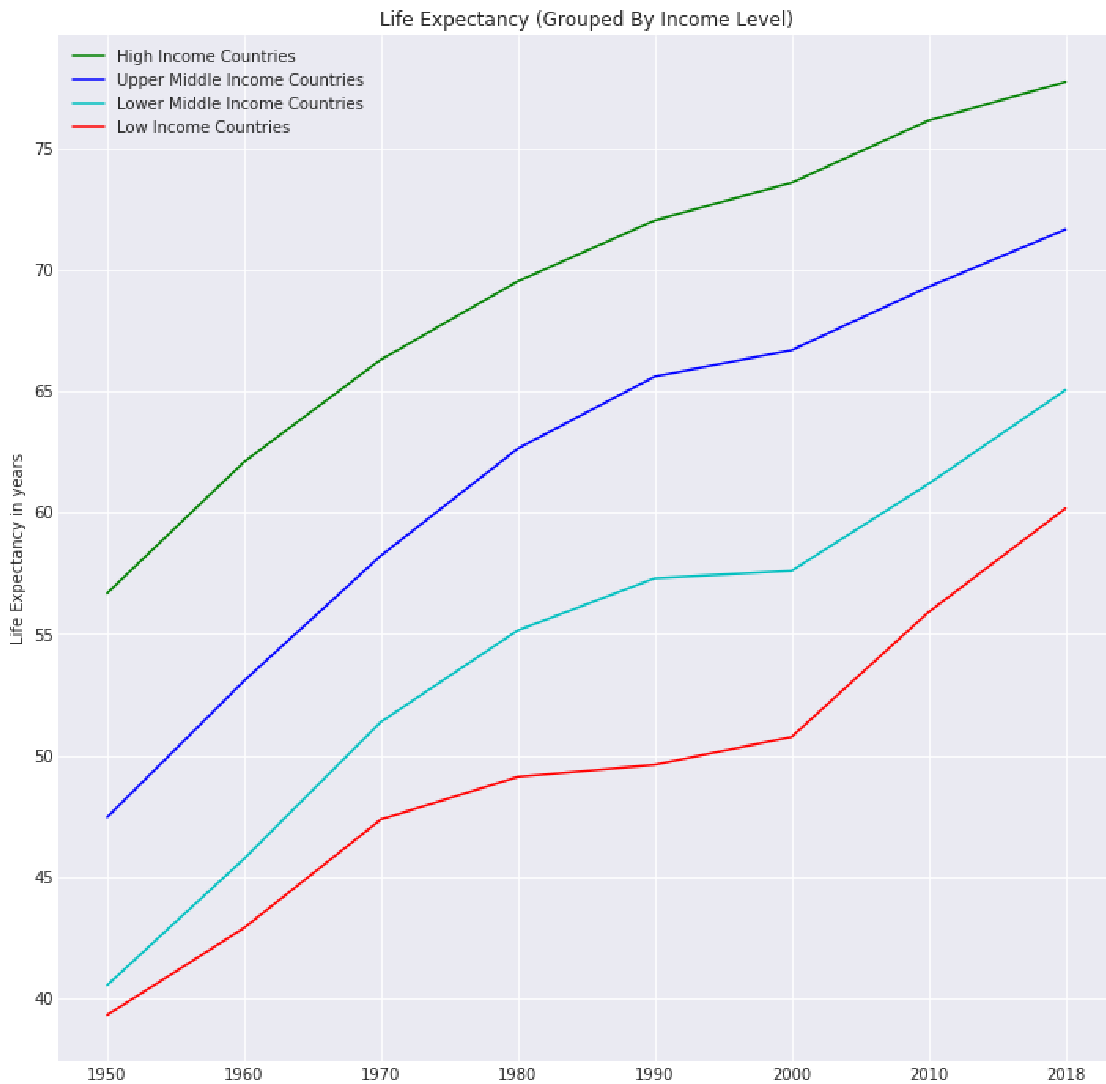
the table above shows that for the high income countries too, life expectancy has been consistently raising. with the standard deviation also getting smaller. 9.5 in the 1950 and 4.33 in 2018. which is pretty good.

Below we are going to plot the mean values for all the 4 group and visually see the changes which occured.

```
In [97]: A = low_income_expectancy.mean()
         B = lower_middle_income_expectancy.mean()
         C = upper_middle_income_expectancy.mean()
         D = high_income_expectancy.mean()
```

```
plt.plot(D, 'g-', label='High Income Countries')
plt.plot(C, 'b-', label='Upper Middle Income Countries')
plt.plot(B, 'c-', label='Lower Middle Income Countries')
plt.plot(A, 'r-', label='Low Income Countries')


from pylab import rcParams
rcParams['figure.figsize'] = 12,12
plt.legend(loc='upper left')
plt.ylabel('Life Expectancy in years')
plt.title('Life Expectancy (Grouped By Income Level)')
```

```
Out[97]: Text(0.5,1,'Life Expectancy (Grouped By Income Level)')
```



so this graph clearly shows that richer the country, longer the life expectancy. since the 1950, we can see that red line (low income countries) are also the countries with the shorted life expectancy. and the life expectancy is directly linked to the income level. richer the country, longer is the life expectancy. But thats not really a suprise.

now let's compare each income group by fertility Rate.

2.0.6 comparaison on Fertility Rate (Number of Babies per woman): How do country from different Income Level differs when its come to the number of babies per woman?

Earlier we created 4 Dataframes for the fertility rate * low_income_birth * lower_middle_income_birth * upper_middle_income_birth * high_income_birth

Babies per Woman In Countries with Low Income (Countries with GNI per Capita between < 995)

In [66]:
```
#checking the dataframe
low_income_birth.head(1)
```

Out[66]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
26	Burundi	6.82	6.95	7.29	7.42	7.51	7.01	6.26	5.53

In [67]:
```
#checking for null Values
low_income_birth.isnull().sum().sum()
```

Out[67]: 0

In [68]:
```
low_income_birth.describe()
```

Out[68]:

	1950	1960	1970	1980	1990	2000	2010	2018
count	6.000000	6.000000	6.000000	6.000000	6.000000	6.000000	6.000000	6.000000
mean	6.458333	6.650000	6.816667	6.963333	7.020000	6.775000	6.221667	5.638333
std	0.704086	0.667263	0.641301	0.655062	0.733975	0.899906	0.952836	0.976390
min	5.400000	5.840000	5.950000	5.950000	5.810000	5.500000	5.020000	4.450000
25%	6.055000	6.102500	6.332500	6.685000	6.657500	6.150000	5.480000	4.922500
50%	6.535000	6.680000	6.940000	6.990000	7.265000	6.985000	6.365000	5.725000
75%	6.985000	7.175000	7.262500	7.317500	7.482500	7.467500	6.770000	6.040000
max	7.250000	7.450000	7.570000	7.840000	7.770000	7.680000	7.490000	7.130000

For this group, the change is relatively small. in 1950 the average number of children per child was 6.45. in 2018 it is 6.45. with a pick in 1990.

Babies per Woman In Countries with Lower Middle Income (Countries with GNI per Capita between 996 and 3895 USD)

```
In [69]: lower_middle_income_birth.head(1)
```

```
Out[69]:        country  1950  1960  1970  1980  1990  2000  2010  2018
         0  Afghanistan  7.57  7.45  7.45  7.45  7.47  7.49  5.82  4.33
```

```
In [70]: # checking null values, there is none
         lower_middle_income_birth.isnull().sum().sum()
```

```
Out[70]: 0
```

```
In [71]: lower_middle_income_birth.describe()
```

```
Out[71]:             1950       1960       1970       1980       1990       2000  \
         count  46.000000  46.000000  46.000000  46.000000  46.000000  46.000000
         mean    6.406522   6.666957   6.742609   6.567826   6.026957   5.281957
         std     0.987257   0.681038   0.773366   1.019141   1.082499   1.214224
         min     1.950000   4.580000   4.320000   2.770000   2.290000   1.990000
         25%     5.992500   6.280000   6.240000   6.250000   5.317500   4.317500
         50%     6.555000   6.785000   6.820000   6.685000   6.195000   5.460000
         75%     6.942500   7.000000   7.235000   7.130000   6.720000   6.070000
         max     7.920000   8.190000   8.230000   8.750000   8.610000   7.490000

                    2010       2018
         count  46.000000  46.000000
         mean    4.575000   4.016522
         std     1.129454   0.989047
         min     1.980000   1.890000
         25%     3.592500   3.342500
         50%     4.830000   4.140000
         75%     5.355000   4.700000
         max     6.590000   5.880000
```

Babies per Woman In Countries with Upper Middle Income (Countries with GNI per Capita between 3895 and 12055 USD)

```
In [72]: upper_middle_income_birth.head(1)
```

```
Out[72]:   country  1950  1960  1970  1980  1990  2000  2010  2018
         3  Angola  7.11  7.48   7.6   7.5  7.25  6.64  6.16  5.55
```

```
In [73]: # checking null values, there is none
         upper_middle_income_birth.isnull().sum().sum()
```

```
Out[73]: 0
```

Babies per Woman In Countries with High Income countries (Countries with GNI per Capita > 12055 USD)

In [74]:
```
high_income_birth.head(1)
```

Out[74]:

	country	1950	1960	1970	1980	1990	2000	2010	2018
1	Albania	5.87	6.49	4.91	3.62	2.98	2.16	1.65	1.71

In [75]:
```
# checking null values, there is none
high_income_birth.isnull().sum().sum()
```

Out[75]: 0

In [76]:
```
high_income_birth.describe()
```

Out[76]:

	1950	1960	1970	1980	1990	2000	\
count	92.000000	92.000000	92.000000	92.000000	92.000000	92.000000	
mean	4.587391	4.550326	4.040652	3.285652	2.730978	2.115435	
std	1.771416	1.843716	1.847032	1.677433	1.265315	0.840647	
min	1.870000	1.910000	1.830000	1.460000	1.300000	1.120000	
25%	2.935000	2.707500	2.370000	2.022500	1.807500	1.500000	
50%	4.490000	4.155000	3.540000	2.515000	2.250000	1.935000	
75%	6.157500	6.450000	5.627500	4.212500	3.240000	2.565000	
max	8.110000	7.560000	8.130000	8.300000	7.170000	5.830000	

	2010	2018
count	92.000000	92.000000
mean	1.995000	1.918913
std	0.669322	0.557554
min	1.190000	1.240000
25%	1.517500	1.570000
50%	1.870000	1.770000
75%	2.222500	2.032500
max	5.210000	4.510000

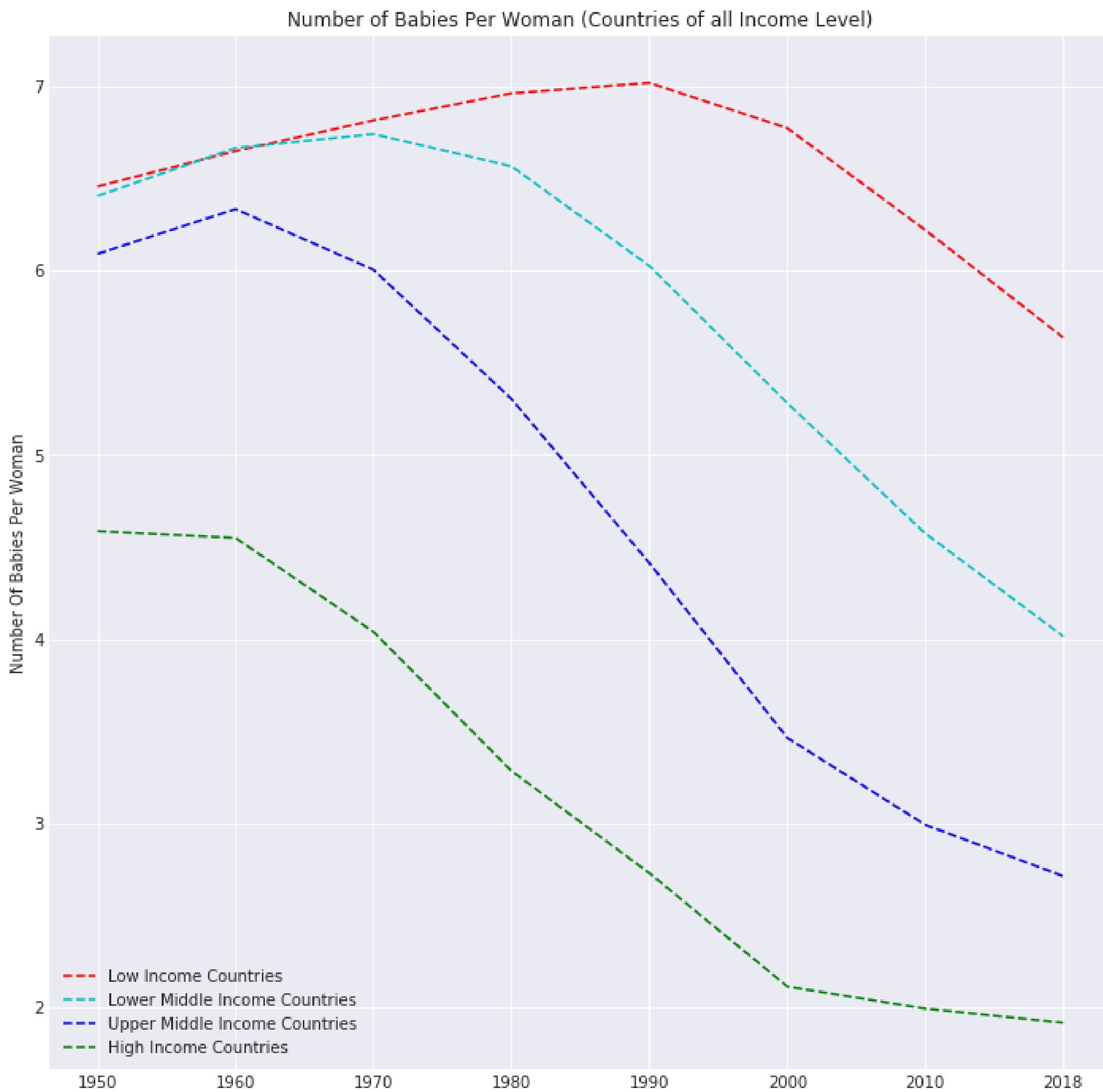
By quicly having a look at the table above, we can se a much shaper decrease in number of birth. from 4.5 in 1950 to 1.9 in 2013. with a shaper decrease from the 1980's.

let's plot all 4 groups to see how the differences and similiraties

In [95]:
```
A = low_income_birth.mean()
B = lower_middle_income_birth.mean()
C = upper_middle_income_birth.mean()
D = high_income_birth.mean()
plt.plot(A, 'r--', label='Low Income Countries')
plt.plot(B, 'c--', label='Lower Middle Income Countries')
plt.plot(C, 'b--', label='Upper Middle Income Countries')
plt.plot(D, 'g--', label='High Income Countries')
from pylab import rcParams
rcParams['figure.figsize'] = 12,12
```

```
plt.legend(loc='lower left')
plt.ylabel('Number Of Babies Per Woman')
plt.title('Number of Babies Per Woman (Countries of all Income Level)')
```

Out[95]: Text(0.5,1,'Number of Babies Per Woman (Countries of all Income Level)')



We can clearly see that since the 1950's there has been a decrease in the number of birth in all countries. up to late 1960's the low income and lower income countries had same numbers of birth. but as time went by, birth in lower middle income countries become lower than countries from the Low Income Group.

so richer countries have longer lives and fewer children. there has been negative correlation between Life expectancy and number of births, at least from the 1950's.

does that impact the economic growth? growth is based upon so many metrics but todays we will just focus on life expectancy and number of birth

2.0.7 comparaison on Growth : So richer countries all have long life expectacncy and fewer babies. How is their growth going going? is there any hope for the future for people from Low Income Countries

- low_income_growth
- lower_middle_income_growth
- upper_middle_income_growth
- high_income_growth

So we can see that richer countries consistently have higher Life Expectancy and Fewer children. But isn't that at some point affecting growth? In some of the richest countries, like Japan, retreat age is being pushed and foreigners are welcome to fill in jobs because nationals are no longer enough. Growth Is dependent on so many things. but is there a relationship between growth and Fertility Rate and the life Expectancy of a country? let's find out in this section

as previously done, we are going to use the data that we grouped. visualize and then draw conclusions

```
In [78]: #checking the dataframe
         low_income_growth.head(1)
```

```
Out[78]:     country   1950  1960  1970  1980  1990  2000  2010  2013
         27  Burundi  0.855  1.47  26.3   6.4  3.63 -1.15  3.98  3.91
```

```
In [79]: #checking for null values
         low_income_growth.isnull().sum().sum()
```

```
Out[79]: 0
```

```
In [80]: lower_middle_income_growth.head(1)
```

```
Out[80]:        country  1950  1960  1970  1980   1990  2000  2010  2013
         0  Afghanistan  1.42  3.37  1.94 -0.28 -0.885  1.74  8.04  4.47
```

```
In [81]: #Checking where null values are
         lower_middle_income_growth.isnull().sum()
```

```
Out[81]: country    0
         1950       0
         1960       0
         1970       0
         1980       0
         1990       0
         2000       0
         2010       1
         2013       4
         dtype: int64
```

```
In [82]: # replacing missing values in 2010 and 2013 with the group mean Growth of the year
         lower_middle_income_growth['2010'].fillna((lower_middle_income_growth['2010'].mean()),
         lower_middle_income_growth['2013'].fillna((lower_middle_income_growth['2013'].mean()),
         lower_middle_income_growth.isnull().sum().sum()
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/generic.py:3660: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self._update_inplace(new_data)
```

```
Out[82]: 0
```

```
In [83]: high_income_growth.isnull().sum()
```

```
Out[83]: country    0
         1950       0
         1960       0
         1970       0
         1980       0
         1990       0
         2000       0
         2010       0
         2013       5
         dtype: int64
```

```
In [84]: #looking for mean growth value for each decade for all the 4 groups
         low_income_growth.mean()
```

```
Out[84]: 1950    2.117500
         1960    3.902333
         1970    8.180500
         1980    1.417667
         1990   -9.010000
         2000    2.975167
         2010    5.713333
         2013   -1.505000
         dtype: float64
```

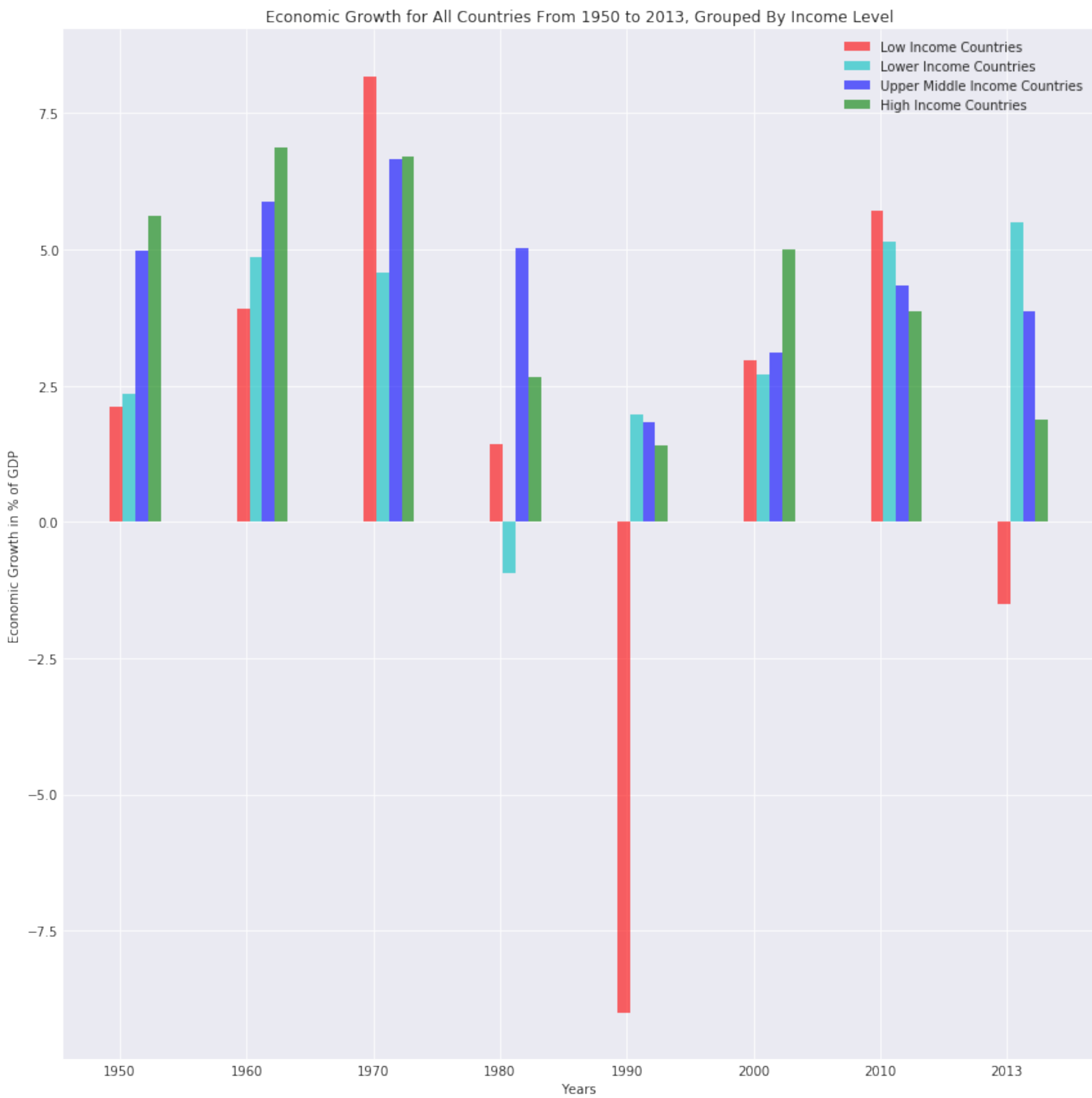
```
In [85]: high_income_growth['2013'].fillna((high_income_growth['2013'].mean()), inplace=True)
         high_income_growth.isnull().sum().sum()
```

```
/opt/conda/lib/python3.6/site-packages/pandas/core/generic.py:3660: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
  self._update_inplace(new_data)
```

```
Out[85]: 0
```

In Order to make a bar chart with the growth from all 4 groups. I simply used looked for the mean value for each decades(as done above). There must be different ways to do this, but since in this case we only have a small number of values, I simply copied/paste them from the cell above to the cell below.

In [98]:
```
# data to plot

n_groups = 8

low_mean_growth = (2.117500,3.902333,8.180500,1.417667, -9.010000,2.975167, 5.713333,-1
lower_mean_growth = (2.354979,4.863750 , 4.566604, -0.938271,1.970963,2.698229,5.142915
upper_mean_growth = (4.969780,5.869163,6.669439,5.017659, 1.820954,3.109122,4.343732, 3
high_mean_growth = (5.617388,6.867168,6.713541,2.651132,1.405147,5.011735, 3.866864, 1.

fig, ax = plt.subplots()

index = np.arange(n_groups)
bar_width = 0.1
opacity = 0.6

rects1 = plt.bar(index, low_mean_growth, bar_width,
                 alpha=opacity, color='r',label='Low Income Countries')
rects2 = plt.bar(index + bar_width,lower_mean_growth, bar_width,
                 alpha=opacity, color='c', label='Lower Income Countries')
rects3 = plt.bar(index + bar_width + bar_width,upper_mean_growth, bar_width,
                 alpha=opacity,  color='b', label='Upper Middle Income Countries')
rects4 = plt.bar(index + bar_width + bar_width + bar_width,high_mean_growth, bar_width,
                 alpha=opacity, color='g', label='High Income Countries')
rcParams['figure.figsize'] = 12,12

ax.set_xlabel('Years')
ax.set_ylabel('Economic Growth in % of GDP')
ax.set_title('Economic Growth for All Countries From 1950 to 2013, Grouped By Income Le
ax.set_xticks(index + bar_width / 4)
ax.set_xticklabels(('1950', '1960', '1970', '1980', '1990', '2000',
                    '2010', '2013'))

ax.legend()
fig.tight_layout()
plt.show()
```




```
In [87]: # checking growth in the low income group
         #looking at the 1990 column in the low income group to understand
         low_income_growth
```

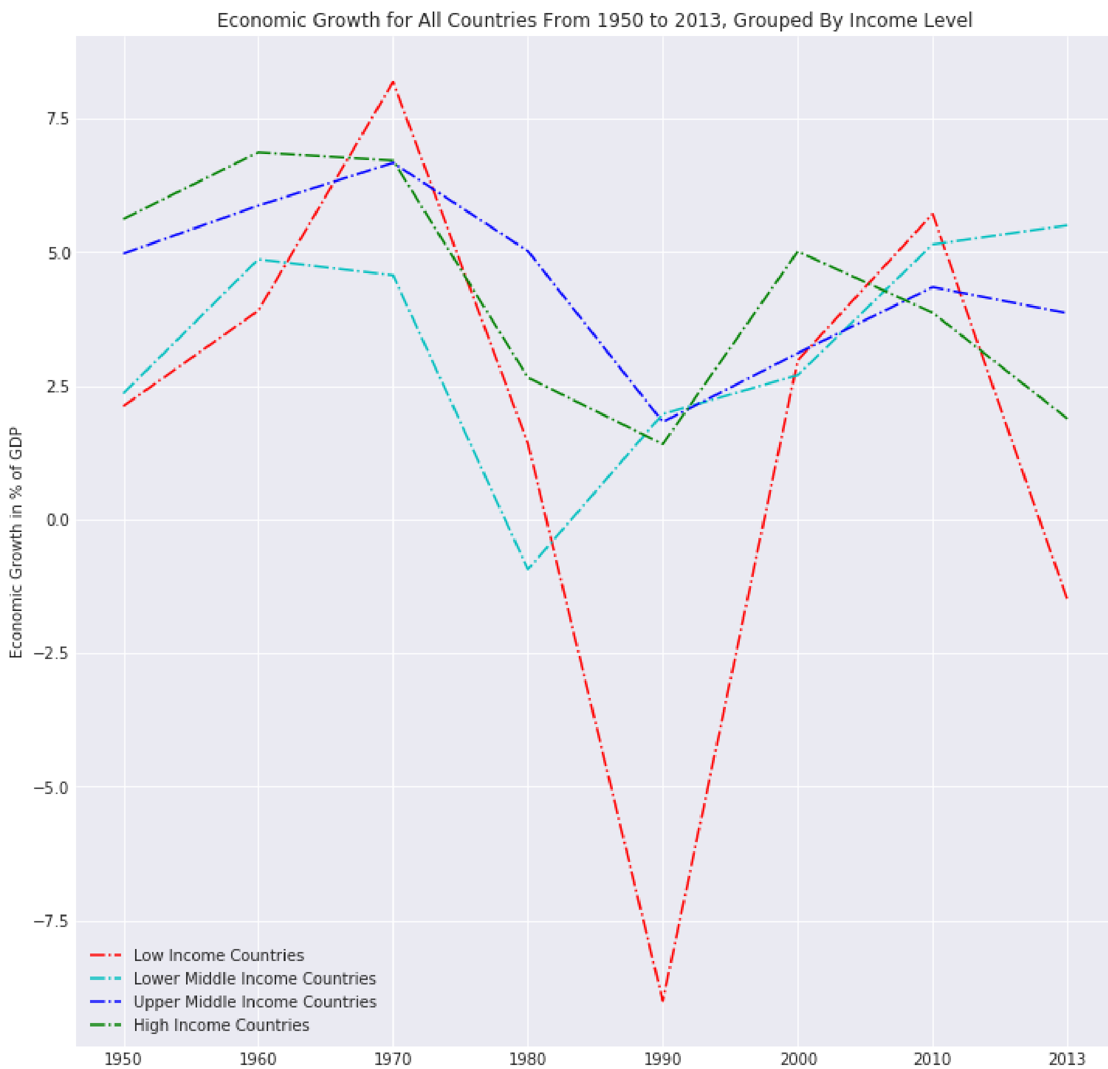
```
Out[87]:                   country   1950   1960    1970   1980   1990    2000  \
         27                Burundi  0.855  1.470  26.300  6.400   3.63  -1.150
         32   Central African Republic  5.200  0.674   4.210 -0.894   3.09   1.720
         38         Congo, Dem. Rep.  1.990  9.540  -0.187  2.410  -6.58  -6.900
         94                Liberia  2.200  2.900   6.410 -6.290 -51.00  22.400
         124                 Niger  1.190  7.310   3.890  5.220  -1.47  -0.779
         155               Somalia  1.270  1.520   8.460  1.660  -1.73   2.560

              2010   2013
```

```
27     3.98   3.91
32     2.46 -36.00
38     7.19   8.11
94     7.26   7.81
124   11.20   4.03
155    2.19   3.11
```

so from the chart above shows growth for each group in the years 1950, 1960, 1970, 1980, 1990, 2000, 2010 and 2013. we can see that the low income group had a huge growth in 1970. and one really visible negative value in 1990. the data looked so strange that I had to look at the data once again. (check the table above) and one big outlier was Liberia with -51.00 in the year 1990. By making a quick google search, I could notice that year the country knew a civil war. my first attempt was to remove this extreme value but since 4 out of 6 countries in that group had negative values that year, I decided to leave the plot as is. https://en.wikipedia.org/wiki/First_Liberian_Civil_War.

apart from negative growth in 1980 for lower middle income countries and another negative value in 2013 for the low income countries in 2013, all groups seemed to have enjoyed growth at different levels. Since I could not really observe any tendencies, I decided to also plot a line graph with the same data. as shown below

```
In [99]: A = low_income_growth.mean()
         B = lower_middle_income_growth.mean()
         C = upper_middle_income_growth.mean()
         D = high_income_growth.mean()
         plt.plot(A, 'r-.', label='Low Income Countries')
         plt.plot(B, 'c-.', label='Lower Middle Income Countries')
         plt.plot(C, 'b-.', label='Upper Middle Income Countries')
         plt.plot(D, 'g-.', label='High Income Countries')
         from pylab import rcParams
         rcParams['figure.figsize'] = 8,8
         plt.legend(loc='lower left')
         plt.ylabel('Economic Growth in % of GDP')
         plt.title('Economic Growth for All Countries From 1950 to 2013, Grouped By Income Level

Out[99]: Text(0.5,1,'Economic Growth for All Countries From 1950 to 2013, Grouped By Income Leve
```



This graphs shows better the more erratic tendencies in growth. the green and blue line which the 2 richest group did not fall below 0 of growth but have benefited for less spectacular number in general. In 2013, which is how far the data is available, we can see that lower middle income are benefiting from the highest growth. But at the opposite of the previous metrics, not patterns can be observed.

Conclusions

- we are at the end of this analysis. we could see that people in richer country enjoyed a longer life in average compared to people with a smaller GDP. And that people in less wealthy countries had more children in average comparing to people in richer countries.
- Life expectancy and fertility rate are negatively correlated. even if this analysis could not show any causation. so this is a mere observation.
- This analysis could only show that economic growth knows more pronounced changes than the other variables. but based on this analysis alone, it is hard to

draw any conclusions on any relationships between longevity, fertiliy and economic growth as a trio.

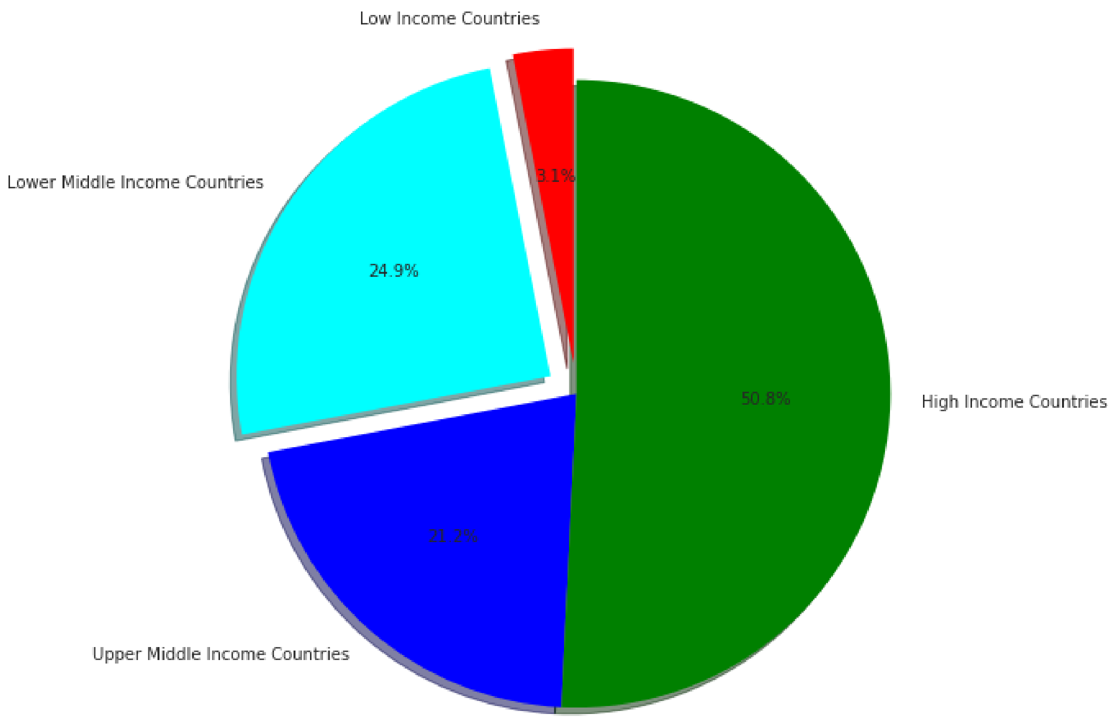
- GDP VS GNI : As previously explained the data used to group the country is the GDP of each country. but instead of using Quartiles,I used the world bank measurement which to be a more realistics measures. But Again, it is not a perfect measure so please take this classification with a grain of salt. the GNI is the measure used in 2018 by the world bank to classify countries by Income.
- 2018 vs 2013 : the data in the life expectancy, number of babies per woman and countries's GDP were all up to 2018. the Growth Dataset only had data up to 2013. But again the grouping was made based on each countries 2018's GDP. since the goal was to look how the different metrics have evolved in the last decades.

Personally this analysis left me a little sad. My secret hope had been that all countries or almost all countries had been benefiting from a steady growth since the 1950' and 1960's. So I went to look one more time at the proportion of each group. and it made me feel a little better.

As shown on the pie chart below, more than 70% of countries are either in High income group (50.8%) or in the upper middle Income countries (21.2%) And only 3.1% of the countries are in the Low income Group. Again please take this classification with a grain of salt. The chart with proportions is below

2.0.8 Proportions of Each Income Level Group

```
In [89]: labels = 'Low Income Countries', 'Lower Middle Income Countries', 'Upper Middle Income
         sizes = [low_income.country.count(),lower_middle_income.country.count() ,
                  upper_middle_income.country.count(),high_income.country.count() ]
         colors = ('red', 'cyan', 'b', 'g')
         explode = (0.1, 0.1, 0, 0)  # only "explode" 1st & 2nd slice

         fig1, ax1 = plt.subplots()

         ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
                 shadow=True, startangle=90, colors=colors)
         rcParams['figure.figsize'] = 5,5
         ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.

         plt.show()
```



This is the end, Thank you.

```
In [90]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[90]: 0
```