Project: Investigate a Dataset (Gapminder World)

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Introduction

> Gapminder has collected a lot of information about how people live heir lives in different countries, racked across the years, and on a umber of different indicators. For this project I selected child mortality, income, life expectancy, and population indicators.
>
> I am going to clean and merge these indicators into one DataFrame then going deep analyzing It tracking the relations between different indicators trying to get insights to make decisions that should make our life better.
>
> Questions to be answered:
>
> Have certain regions of the world been growing in selected indicators better than others?
>
> Is child mortality related to any other indicators?
>
> Is life expectancy child mortality related to any other indicators?
>
> Is Income related to population?

Data Wrangling

Asessing and cleaning Data

In [73]:
```
# Importing packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import datetime as dt
sns.set_style('darkgrid')

# Loading data and printing out a few lines.
df1 = pd.read_csv('child_mortality_0_5_year_olds_dying_per_1000_born.csv')
df2 = pd.read_csv('income_per_person_gdppercapita_ppp_inflation_adjusted (1).csv')
df3 = pd.read_csv('life_expectancy_years (1).csv')
df4 = pd.read_csv('population_total.csv')
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 195 entries, 0 to 194
Columns: 302 entries, country to 2100
dtypes: float64(301), object(1)
memory usage: 460.2+ KB
```

In [74]:
```
# Transposing year rows and renaming the value columns
data_files = [df1, df2, df3, df4]
names = ['child_mortality','income','life_expectancy','population']
i = 0
names = ['child_mortality','income','life_expectancy','population']
for df in data_files:
    df = df.melt(['country'], var_name='year')
    df = df.rename(columns = {'value': names[i]}, inplace = False)
    data_files[i] = df
    i += 1
df1, df2, df3, df4 = data_files
```

In [75]:
```
df1.head() # Checking
```

Out[75]:

	country	year	child_mortality
0	Afghanistan	1800	469.0
1	Albania	1800	375.0
2	Algeria	1800	460.0
3	Andorra	1800	NaN
4	Angola	1800	486.0

In [76]:
```
# Merging data files in one data file
dfm1= pd.merge(df1,df2,on=['year', 'country'], how= 'left')
dfm2 = pd.merge(dfm1,df3,on=['year', 'country'], how= 'left')
df = pd.merge(dfm2,df4,on=['year', 'country'], how= 'left')
```

In [77]:
```
df.head() #checking
```

Out[77]:

	country	year	child_mortality	income	life_expectancy	population
0	Afghanistan	1800	469.0	603.0	28.2	3280000
1	Albania	1800	375.0	667.0	35.4	400000
2	Algeria	1800	460.0	715.0	28.8	2500000
3	Andorra	1800	NaN	1200.0	NaN	2650
4	Angola	1800	486.0	618.0	27.0	1570000

In [78]:
```
# Getting the dataset information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 58695 entries, 0 to 58694
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   country          58695 non-null  object
 1   year             58695 non-null  object
 2   child_mortality  57045 non-null  float64
 3   income           46513 non-null  float64
 4   life_expectancy  55528 non-null  float64
 5   population       58695 non-null  int64
dtypes: float64(3), int64(1), object(2)
memory usage: 3.1+ MB
```

Data has 58695 rows and 4 columns, child mortality represnets dead childs below age 5 per 1.000 births so it should be converted into intg.

In [79]:
```
# Checking for null values and duplicates
df.isnull().sum()
```

Out[79]:
```
country                0
year                   0
child_mortality     1650
income             12182
life_expectancy     3167
population             0
dtype: int64
```

Data has alot of null values that shouldn't be dropped because number of countries will be decreased from 195 to 187! It is better to fill nun values with zeros.

In [80]:
```
# Dealing with null values
df.fillna(0, inplace= True)
```

In [81]:
```
# Checking
df.isnull().sum()
```

Out[81]:
```
country            0
year               0
child_mortality    0
income             0
life_expectancy    0
population         0
dtype: int64
```

In [82]:
```
# Changing the type of the child mortality column data into intg
df.child_mortality=df.child_mortality.astype(int)
```

In [83]:
```
# Checking
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 58695 entries, 0 to 58694
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   country          58695 non-null  object
 1   year             58695 non-null  object
 2   child_mortality  58695 non-null  int32
 3   income           58695 non-null  float64
 4   life_expectancy  58695 non-null  float64
 5   population       58695 non-null  int64
dtypes: float64(2), int32(1), int64(1), object(2)
memory usage: 2.9+ MB
```

In [84]:
```
# Checking for duplicate rows
df.duplicated().sum()
```

Out[84]: 0

It is clear that data has no toataly duplicate rows

In [85]:
```
# Exploring unique values
df.nunique()
```

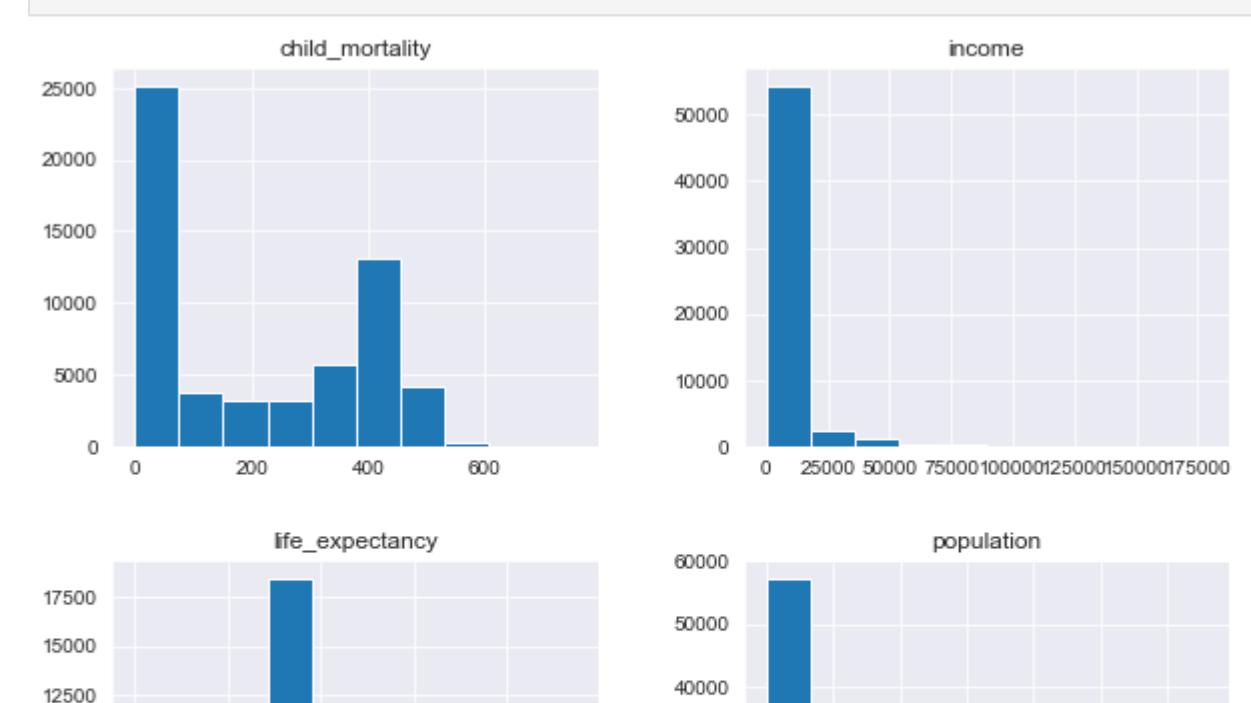
Out[85]:
```
country             195
year                301
child_mortality     630
income             2418
life_expectancy     851
population         4750
dtype: int64
```

In [86]:
```
# Getting some statistical info
df.describe()
```

Out[86]:

	child_mortality	income	life_expectancy	population
count	58695.000000	58695.000000	58695.000000	5.869500e+04
mean	203.540148	5094.384241	50.174385	2.328525e+07
std	186.049102	12169.372391	24.242602	1.007173e+08
min	0.000000	0.000000	0.000000	6.450000e+02
25%	13.000000	530.000000	31.700000	4.220000e+05
50%	162.000000	1190.000000	44.600000	2.610000e+06
75%	400.500000	3410.000000	73.500000	1.080000e+07
max	756.000000	179000.000000	94.800000	1.650000e+09

In [87]:
```
# Visulizing data
df.hist(figsize= (10,8));
```



In [88]:
```
# Correlation
df.corr()
```

Out[88]:

	child_mortality	income	life_expectancy	population
child_mortality	1.000000	-0.295074	-0.683699	-0.140056
income	-0.295074	1.000000	0.245651	0.006699
life_expectancy	-0.683699	0.245651	1.000000	0.172869
population	-0.140056	0.006699	0.172869	1.000000

It seems that there is a correlation between income and child mortality (inverse relation).

Exploratory Data Analysis

Research Question 1 (Have certain regions of the world been growing in selected indicators better than others?)

In [89]:
```
# Setting the country as the index
df.set_index('country', inplace= True)
```

In [90]:
```
df.head() # Checking
```

Out[90]:

	year	child_mortality	income	life_expectancy	population
country					
Afghanistan	1800	469	603.0	28.2	3280000
Albania	1800	375	667.0	35.4	400000
Algeria	1800	460	715.0	28.8	2500000
Andorra	1800	0	1200.0	0.0	2650
Angola	1800	486	618.0	27.0	1570000

In [91]:
```
# Working with the mean values of indicators over years
df_means = df.groupby(['country']).mean()
df_m = df_means
df_m
```

Out[91]:

	child_mortality	income	life_expectancy	population
country				
Afghanistan	292.249169	1133.591362	45.070664	2.408907e+07
Albania	203.362126	3005.966777	56.954153	1.506748e+06
Algeria	252.149502	4105.006645	52.704983	2.416276e+07
Andorra	4.794020	13295.880399	12.720930	3.167442e+04
Angola	296.455150	2065.936877	45.443189	3.171944e+07
...	...	...	...	...
Venezuela	202.418605	5376.910299	54.572093	1.476439e+07
Vietnam	215.249169	1733.754153	52.309967	4.791528e+07
Yemen	319.956811	1449.521595	43.551827	1.736767e+07
Zambia	242.591362	1345.093023	48.079734	1.555402e+07
Zimbabwe	222.056478	1177.813953	48.557475	9.335030e+06

195 rows × 4 columns

In [92]:
```
df_m.describe()
```

Out[92]:

	child_mortality	income	life_expectancy	population
count	195.000000	195.000000	195.000000	1.950000e+02
mean	203.540148	5094.384241	50.174385	2.328525e+07
std	68.302423	5268.751175	12.821073	8.134344e+07
min	2.348837	0.000000	0.000000	8.513322e+02
25%	167.500000	1388.029900	47.538206	1.219176e+06
50%	218.139535	3127.451827	52.095349	5.045389e+06
75%	251.524917	6847.807309	56.529236	1.726764e+07
max	330.468439	32121.328904	67.243854	7.993920e+08

In [93]:
```
df_m.idxmax()[1:4]
```

Out[93]:
```
income               Qatar
life_expectancy     Norway
population           China
dtype: object
```

In [94]:
```
df_m.child_mortality.idxmin()
```

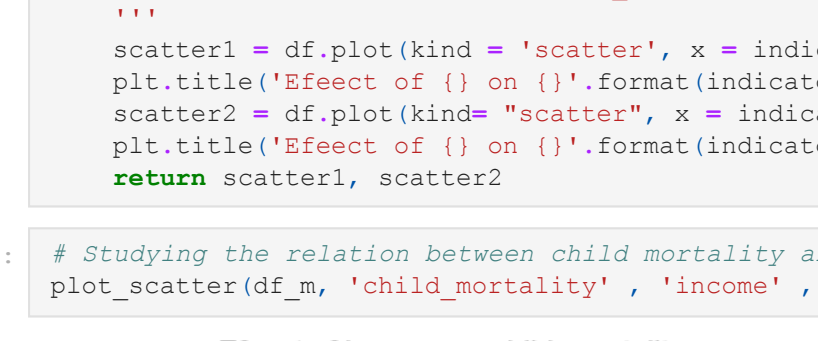
Out[94]: 'Monaco'

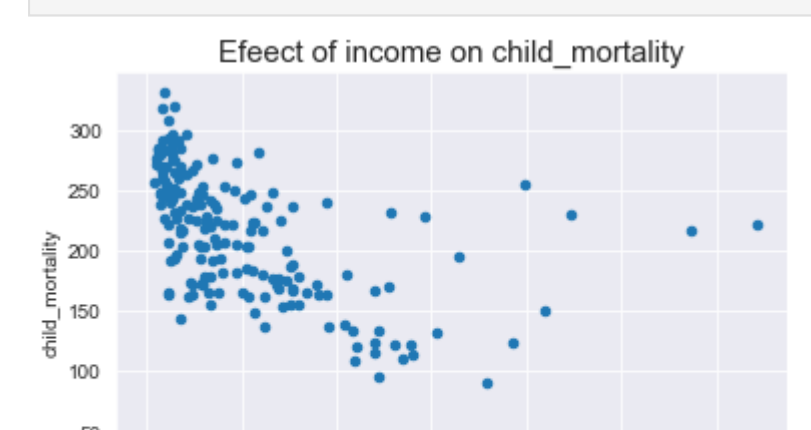
From the past calculations Qatar has the highest mean income level, Norway has the highest mean life expectancy level, China has the highest population levels, Monaco has the least number of child mortalities below age 5 per 1.000 births.

Research Question 2 (Is child mortality related to any other indicators?)

In [95]:
```
# Creating a function that plot the scatter relation between given indicators
def plot_scatter(df, indicator_effected ,indicator1, indicator2):
    '''
    Input data: df DataFrame, indicator_effected, indicator1, indicator2
    Output: two figures
        1-Relation between indicator_effected and indicator1
        2-Relation between indicator_effected and indicator2
    '''
    scatter1 = df.plot(kind = 'scatter', x = indicator1, y = indicator_effected)
    plt.title('Efeect of {} on {}'.format(indicator1, indicator_effected ), fontsize = 15)
    scatter2 = df.plot(kind= "scatter", x = indicator2, y = indicator_effected)
    plt.title('Efeect of {} on {}'.format(indicator2, indicator_effected), fontsize = 15)
    return scatter1, scatter2
```

In [96]:
```
# Studying the relation between child mortality and other indicators
plot_scatter(df_m, 'child_mortality' , 'income' , 'population');
```





Increase in income decreases child mortality. population increase seems to have no strong effect on child mortality.

Why not specefying the country of the higest and lowst level of child mortalities to see what is there on small scale!

In [97]:
```
# Getting the country with the lowst and higest mean levels of child mortality
df_m.child_mortality.idxmax(), df_m.child_mortality.idxmin()
```

Out[97]: ('Sierra Leone', 'Monaco')

In [104...
```
# Specifying the data to the country Monaco
df_Monaco = df_m.query('country == "Monaco"')
# Comparing between moncao's mean income and the mean income of all countires
df_Monaco['income'] > df_m['income'].mean()
```

Out[104...
```
country
Monaco     True
Name: income, dtype: bool
```

In [105...
```
# Comparing between moncao's mean population and the mean population of all countires
df_Monaco['population'] < df_m['population'].mean()
```

Out[105...
```
country
Monaco     True
Name: population, dtype: bool
```

Monaca which is the country that has the lowst mean value of child mortality has an income mean grater than the mean of other countries income means and a population mean less than the mean of other countries population means.

In [106...
```
# Specifying the data to the country Sierra Leone
df_sierra = df_m.query('country == "Sierra Leone"')
# Comparing between df_sierra's mean income and the mean income of all countires
df_sierra['income'] > df_m['income'].mean()
```

Out[106...
```
country
Sierra Leone     False
Name: income, dtype: bool
```

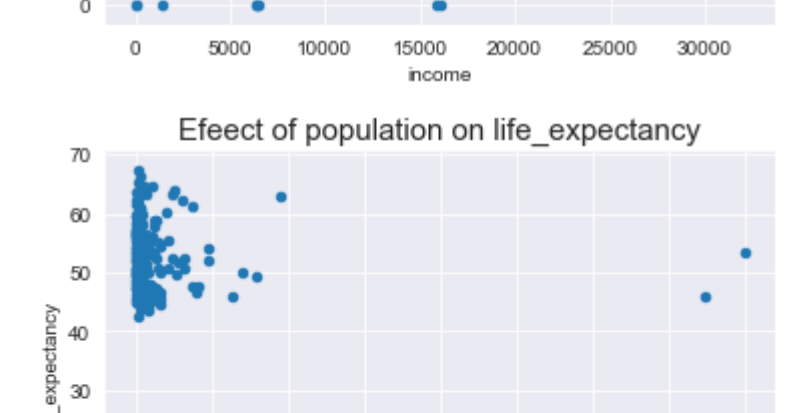
In [113...
```
# Comparing between moncao's mean population and the mean population of all countires
df_sierra['population'] < df_m['population'].mean()
```

Out[113...
```
country
Sierra Leone     True
Name: population, dtype: bool
```

Now we can say that it is clear on the large scale of all countries and on the small scale of the two countires of highest and lowst level of child mortality that increase in income decreases the child mortality, but increase in population has no strong effect on it.

Research Question 3 (Is life expectancy child mortality related to any other indicators?)

In [102...
```
# Studying the relation between life expectancy and other indicators
plot_scatter(df_m, 'life_expectancy' , 'income' , 'population');
```



Life expectancy increases by the increase in income. population increase seems to have an inverse effect on life expectancy.

In [117...
```
# Getting the country with the lowst and higest mean levels of Life expectancy
df_m.life_expectancy.idxmax(), df_m.life_expectancy.idxmin()
```

Out[117... ('Norway', 'Holy See')

In [118...
```
# Specifying the data to the country Monaco
df_Norway = df_m.query('country == "Norway"')
# Comparing between moncao's mean income and the mean income of all countires
df_Norway['income'] > df_m['income'].mean()
```

Out[118...
```
country
Norway     True
Name: income, dtype: bool
```

In [120...
```
# Comparing between Norway's mean population and the mean population of all countires
df_Norway['population'] < df_m['population'].mean()
```

Out[120...
```
country
Norway     True
Name: population, dtype: bool
```

Norway which is the country that has the highest mean value of life expectancy has an income mean grater than the mean of other countries income means and a population mean less than the mean of other countries population means.

In [121...
```
# Specifying the data to the country Holy See
df_HolySee = df_m.query('country == "Sierra Leone"')
# Comparing between Holy See's mean income and the mean income of all countires
df_HolySee['income'] > df_m['income'].mean()
```

Out[121...
```
country
Sierra Leone     False
Name: income, dtype: bool
```

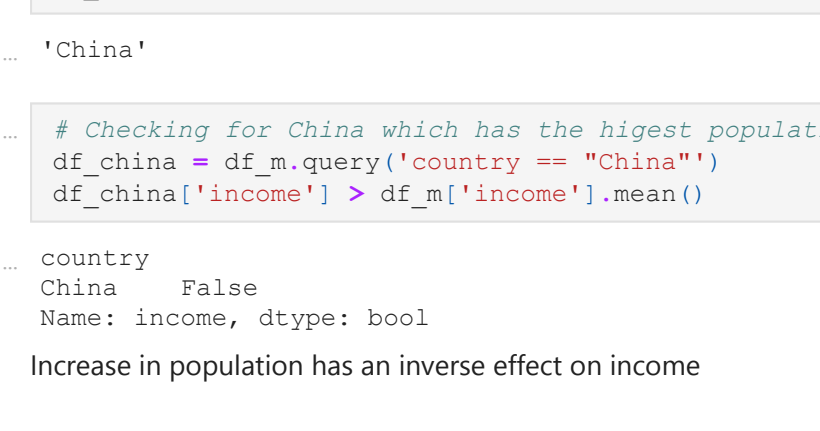
In [122...
```
# Comparing between Holy See's mean population and the mean population of all countires
df_HolySee['population'] < df_m['population'].mean()
```

Out[122...
```
country
Sierra Leone     True
Name: population, dtype: bool
```

Now we can say that it is clear on the large scale of all countries and on the small scale of the two countires of highest and lowst level of life expectancy that increase in income increases the life expectancy , but increase in population has no strong effect on it.

Research Question 4 (Is Income related to population?)

In [138...
```
# Relation between income and population
df_m.plot(kind = 'scatter', x = "population", y = "income")
plt.title('Efeect of {} on {}'.format("population", "income"), fontsize = 15);
```



In [135...
```
# Getting the country with the lowst and higest mean levels of population
df_m.population.idxmax()
```

Out[135... 'China'

In [136...
```
# Checking for China which has the higest population mean
df_china = df_m.query('country == "China"')
df_china['income'] > df_m['income'].mean()
```

Out[136...
```
country
China     False
Name: income, dtype: bool
```

Increase in population has an inverse effect on income

Conclusions

After analysis of the data we concluded the next outcomes:

Qatar has the highest mean income level, Norway has the highest mean life expectancy level, China has the highest population mean levels, and Monaco has the least number of child mortalities below age 5 per 1.000 births.

An increase in income decreases child mortality, but an increase in population has no strong effect on it.

An increase in income increases life expectancy, but an increase in population has no strong effect on it.

An increase in population has an inverse effect on income.

References

How can I use for loop with melt and rename in pandas?

Transpose Dataframe Columns into Rows

Joins in Pandas

Get the index of minimum value in DataFrame column How can I use for loop with melt and rename in pandas?