Project

February 7, 2021

1 Life expectancy Analysis

1.1 An investigation of longevity and the social factors that determine a longer life

Dataset used was extract from Gapminder World

1.1.1 INTRODUCTION

The main objective of this investigation is to find out which economic and social factors affects directly in the longevity of people of different countries.

From this objective arise different questions like: -Wich variables predict longevity? -Is there a direct correlation between goverment expenditure and life expetency? -Do social economic factors such as inequality and corruption affect the life of citizens?

For answering these questions, i am going to analyze how corruption, education, freedom, economic growth, health among others are linked to life expectancy. Using data from 2015 to 2017 of each varible gather on gapminder.com

Variable's dictionary For the research i will be using the next 9 variables **Life_expect**: The average number of years a newborn child would live if current mortality patterns were to stay the same. **corruption perception_index**: Transparency international's score of perceptions of corruption. Higher number less corruption. **health_spend**: The average health expenditure per person paid by goverment, PPP. **education_exp**: Goverment expenditure per student in primary school. **freedix**: Average of political rigths and civil liberties. 1(Most free) 7 (Least Free) **gdp_growth**: GDP per capita yearly growth. **gini**: gini index. **10per_richest**: Income share that the richest 10% accrues. **Military_exp**: Goverment expenditure on the armed forces

2 DATA WRANGLING

[ ]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[4]:
```
df = pd.read_csv('/Users/braul/Downloads/dataset_3.csv', sep= ";", index_col␣
↪='country')
```

[5]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 177 entries, Afghanistan to Zimbabwe
Data columns (total 25 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   life_expect_2015                  177 non-null    float64
 1   life_expect_2016                  177 non-null    float64
 2   life_expect_2017                  177 non-null    float64
 3   Corruption perception_index_2015  165 non-null    float64
 4   Corruption perception_index_2016  173 non-null    float64
 5   Corruption perception_index_2017  177 non-null    int64
 6   Education_exp_2015                151 non-null    float64
 7   Education_exp_2016                151 non-null    float64
 8   Education_exp_2017                151 non-null    float64
 9   freedix_2015                      177 non-null    float64
 10  freedix_2016                      177 non-null    float64
 11  freedix_2017                      177 non-null    float64
 12  gdp_growth_2015                   177 non-null    float64
 13  gdp_growth_2016                   177 non-null    float64
 14  gdp_growth_2017                   177 non-null    float64
 15  gini_2015                         177 non-null    float64
 16  gini_2016                         177 non-null    float64
 17  gini_2017                         177 non-null    float64
 18  health_spend                      174 non-null    float64
 19  10per_richest_2015                156 non-null    float64
 20  10per_richest_2016                156 non-null    float64
 21  10per_richest_2017                156 non-null    float64
 22  Military_exp_2015                 163 non-null    float64
 23  Military_exp_2016                 163 non-null    float64
 24  Military_exp_2017                 163 non-null    float64
dtypes: float64(24), int64(1)
memory usage: 36.0+ KB
```

As we can see in the info, there are some columns with no values, for fix this problem i'm going to use the mean of each column to fill the empty spaces; in this way we´re not going to have issues to analyze the information correctly

[6]:
```
#Calculating the mean
mean1 = round(df['Corruption perception_index_2015'].mean(), 2)
mean2 = round(df['Corruption perception_index_2016'].mean(), 2)
mean3 = round(df['Education_exp_2015'].mean(), 2)
mean4 = round(df['Education_exp_2016'].mean(), 2)
mean5 = round(df['Education_exp_2017'].mean(), 2)
mean6 = round(df['health_spend'].mean(), 2)
mean7 = round(df['10per_richest_2015'].mean(), 2)
mean8 = round(df['10per_richest_2016'].mean(), 2)
mean9 = round(df['10per_richest_2017'].mean(), 2)
mean10 = round(df['Military_exp_2015'].mean(), 2)
```

```
mean11 = round(df['Military_exp_2016'].mean(), 2)
mean12 = round(df['Military_exp_2017'].mean(), 2)

df['Corruption perception_index_2015'] = df['Corruption perception_index_2015'].
 ↪fillna(mean1)
df['Corruption perception_index_2016'] = df['Corruption perception_index_2016'].
 ↪fillna(mean2)
df['Education_exp_2015'] = df['Education_exp_2015'].fillna(mean3)
df['Education_exp_2016'] = df['Education_exp_2016'].fillna(mean4)
df['Education_exp_2017'] = df['Education_exp_2017'].fillna(mean5)
df['health_spend'] = df['health_spend'].fillna(mean6)
df['10per_richest_2015'] = df['10per_richest_2015'].fillna(mean7)
df['10per_richest_2016'] = df['10per_richest_2016'].fillna(mean8)
df['10per_richest_2017'] = df['10per_richest_2017'].fillna(mean9)
df['Military_exp_2015'] = df['Military_exp_2015'].fillna(mean10)
df['Military_exp_2016'] = df['Military_exp_2016'].fillna(mean11)
df['Military_exp_2017'] = df['Military_exp_2017'].fillna(mean12)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 177 entries, Afghanistan to Zimbabwe
Data columns (total 25 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
 0   life_expect_2015                  177 non-null    float64
 1   life_expect_2016                  177 non-null    float64
 2   life_expect_2017                  177 non-null    float64
 3   Corruption perception_index_2015  177 non-null    float64
 4   Corruption perception_index_2016  177 non-null    float64
 5   Corruption perception_index_2017  177 non-null    int64
 6   Education_exp_2015                177 non-null    float64
 7   Education_exp_2016                177 non-null    float64
 8   Education_exp_2017                177 non-null    float64
 9   freedix_2015                      177 non-null    float64
 10  freedix_2016                      177 non-null    float64
 11  freedix_2017                      177 non-null    float64
 12  gdp_growth_2015                   177 non-null    float64
 13  gdp_growth_2016                   177 non-null    float64
 14  gdp_growth_2017                   177 non-null    float64
 15  gini_2015                         177 non-null    float64
 16  gini_2016                         177 non-null    float64
 17  gini_2017                         177 non-null    float64
 18  health_spend                      177 non-null    float64
 19  10per_richest_2015                177 non-null    float64
 20  10per_richest_2016                177 non-null    float64
 21  10per_richest_2017                177 non-null    float64
 22  Military_exp_2015                 177 non-null    float64
```

```
 23   Military_exp_2016                  177 non-null    float64
 24   Military_exp_2017                  177 non-null    float64
dtypes: float64(24), int64(1)
memory usage: 36.0+ KB
```

Once we completed our missing information, we are going to create an easier way to analize our data. Since we have 3 years of each variable; it could be useful to merge them into 1 single column that describe the average of each factor

[7]:
```
#CREADOR DE COLUMNAS CON PROMEDIOS
df['life_expect'] = ((df['life_expect_2015'] + df['life_expect_2016'] +␣
 ↪df['life_expect_2017'])/3)
df['corruption perception_index'] = ((df['Corruption perception_index_2015'] +␣
 ↪df['Corruption perception_index_2016']
                                          + df['Corruption perception_index_2017'])/
 ↪3)
df['education_exp'] = ((df['Education_exp_2015'] + df['Education_exp_2016'] +␣
 ↪df['Education_exp_2017'])/3)
df['freedix'] = ((df['freedix_2015'] + df['freedix_2016'] + df['freedix_2017'])/
 ↪3)
df['gdp_growth'] = ((df['gdp_growth_2015'] + df['gdp_growth_2016'] +␣
 ↪df['gdp_growth_2017'])/3)
df['gini'] = ((df['gini_2015'] + df['gini_2016'] + df['gini_2017'])/3)
df['10per_richest'] = ((df['10per_richest_2015'] + df['10per_richest_2016'] +␣
 ↪df['10per_richest_2017'])/3)
df[' Military_exp'] = ((df['Military_exp_2015'] + df['Military_exp_2016'] +␣
 ↪df['Military_exp_2017'])/3)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 177 entries, Afghanistan to Zimbabwe
Data columns (total 33 columns):
 #    Column                             Non-Null Count  Dtype
---   ------                             --------------  -----
 0    life_expect_2015                   177 non-null    float64
 1    life_expect_2016                   177 non-null    float64
 2    life_expect_2017                   177 non-null    float64
 3    Corruption perception_index_2015   177 non-null    float64
 4    Corruption perception_index_2016   177 non-null    float64
 5    Corruption perception_index_2017   177 non-null    int64
 6    Education_exp_2015                 177 non-null    float64
 7    Education_exp_2016                 177 non-null    float64
 8    Education_exp_2017                 177 non-null    float64
 9    freedix_2015                       177 non-null    float64
 10   freedix_2016                       177 non-null    float64
 11   freedix_2017                       177 non-null    float64
 12   gdp_growth_2015                    177 non-null    float64
 13   gdp_growth_2016                    177 non-null    float64
```

```
 14   gdp_growth_2017                  177 non-null    float64
 15   gini_2015                        177 non-null    float64
 16   gini_2016                        177 non-null    float64
 17   gini_2017                        177 non-null    float64
 18   health_spend                     177 non-null    float64
 19   10per_richest_2015               177 non-null    float64
 20   10per_richest_2016               177 non-null    float64
 21   10per_richest_2017               177 non-null    float64
 22   Military_exp_2015                177 non-null    float64
 23   Military_exp_2016                177 non-null    float64
 24   Military_exp_2017                177 non-null    float64
 25   life_expect                      177 non-null    float64
 26   corruption perception_index      177 non-null    float64
 27   education_exp                    177 non-null    float64
 28   freedix                          177 non-null    float64
 29   gdp_growth                       177 non-null    float64
 30   gini                             177 non-null    float64
 31   10per_richest                    177 non-null    float64
 32    Military_exp                    177 non-null    float64
dtypes: float64(32), int64(1)
memory usage: 47.0+ KB
```

Now that we have the mean of every column we will drop the series times as we are not going to use them.

[8]:
```python
del df['life_expect_2015']
del df['life_expect_2016']
del df['life_expect_2017']
del df['Corruption perception_index_2015']
del df['Corruption perception_index_2016']
del df['Corruption perception_index_2017']
del df['Education_exp_2015']
del df['Education_exp_2016']
del df['Education_exp_2017']
del df['freedix_2015']
del df['freedix_2016']
del df['freedix_2017']
del df['gdp_growth_2015']
del df['gdp_growth_2016']
del df['gdp_growth_2017']
del df['gini_2015']
del df['gini_2016']
del df['gini_2017']
del df['10per_richest_2015']
del df['10per_richest_2016']
del df['10per_richest_2017']
del df['Military_exp_2015']
del df['Military_exp_2016']
```

```python
del df['Military_exp_2017']
```

Now our data is complete, clean and ready to analyze. To check this we can use describe and info as follows:

[14]:
```python
df.describe()
```

[14]:
```
       health_spend  life_expect  corruption perception_index  education_exp  \
count    177.000000   177.000000                   177.000000     177.000000
mean     712.544859    72.479473                    42.611902       0.072323
std     1047.657012     7.358934                    19.011440       0.063873
min        0.000000    51.500000                     9.000000       0.000000
25%       50.300000    67.700000                    28.666667       0.000000
50%      260.000000    73.533333                    38.000000       0.073333
75%      830.000000    78.100000                    53.666667       0.116800
max     5690.000000    84.633333                    90.000000       0.332667

          freedix  gdp_growth        gini  10per_richest   Military_exp
count  177.000000  177.000000  177.000000     177.000000     177.000000
mean     3.545198    2.929712   38.749153      13.259454       0.017145
std      2.023886    2.313622    7.595394      11.272352       0.015659
min      1.000000   -6.806667   24.933333       0.000000       0.000000
25%      1.666667    1.550000   32.800000       0.000000       0.009327
50%      3.166667    2.630000   38.400000      12.866667       0.014267
75%      5.500000    4.066667   43.200000      22.833333       0.020000
max      7.000000   19.906667   63.033333      41.666667       0.111233
```

[15]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 177 entries, Afghanistan to Zimbabwe
Data columns (total 10 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   health_spend                  177 non-null    float64
 1   life_expect                   177 non-null    float64
 2   corruption perception_index   177 non-null    float64
 3   education_exp                 177 non-null    float64
 4   freedix                       177 non-null    float64
 5   gdp_growth                    177 non-null    float64
 6   gini                          177 non-null    float64
 7   10per_richest                 177 non-null    float64
 8    Military_exp                 177 non-null    float64
 9   corruptions_levels            177 non-null    category
dtypes: category(1), float64(9)
memory usage: 14.2+ KB
```

3 Exploratory Data Analysis

3.0.1 Wich variables predict the longevity?

In order to watch how the different variables interact with life expectancy, we are going to model the correlation and make some scatter plots.

[79]:
```
df.describe()
```

[79]:

	health_spend	life_expect	corruption perception_index	education_exp
count	177.000000	177.000000	177.000000	177.000000
mean	712.544859	72.479473	42.611902	0.072323
std	1047.657012	7.358934	19.011440	0.063873
min	0.000000	51.500000	9.000000	0.000000
25%	50.300000	67.700000	28.666667	0.000000
50%	260.000000	73.533333	38.000000	0.073333
75%	830.000000	78.100000	53.666667	0.116800
max	5690.000000	84.633333	90.000000	0.332667

	freedix	gdp_growth	gini	10per_richest	Military_exp
count	177.000000	177.000000	177.000000	177.000000	177.000000
mean	3.545198	2.929712	38.749153	13.259454	0.017145
std	2.023886	2.313622	7.595394	11.272352	0.015659
min	1.000000	-6.806667	24.933333	0.000000	0.000000
25%	1.666667	1.550000	32.800000	0.000000	0.009327
50%	3.166667	2.630000	38.400000	12.866667	0.014267
75%	5.500000	4.066667	43.200000	22.833333	0.020000
max	7.000000	19.906667	63.033333	41.666667	0.111233

[16]:
```
df.corr()
```

[16]:

	health_spend	life_expect
health_spend	1.000000	0.608001
life_expect	0.608001	1.000000
corruption perception_index	0.791839	0.658276
education_exp	0.305043	0.401120
freedix	-0.532935	-0.488161
gdp_growth	-0.323026	-0.243741
gini	-0.373218	-0.408390
10per_richest	0.285947	0.467238
Military_exp	-0.042418	0.118763

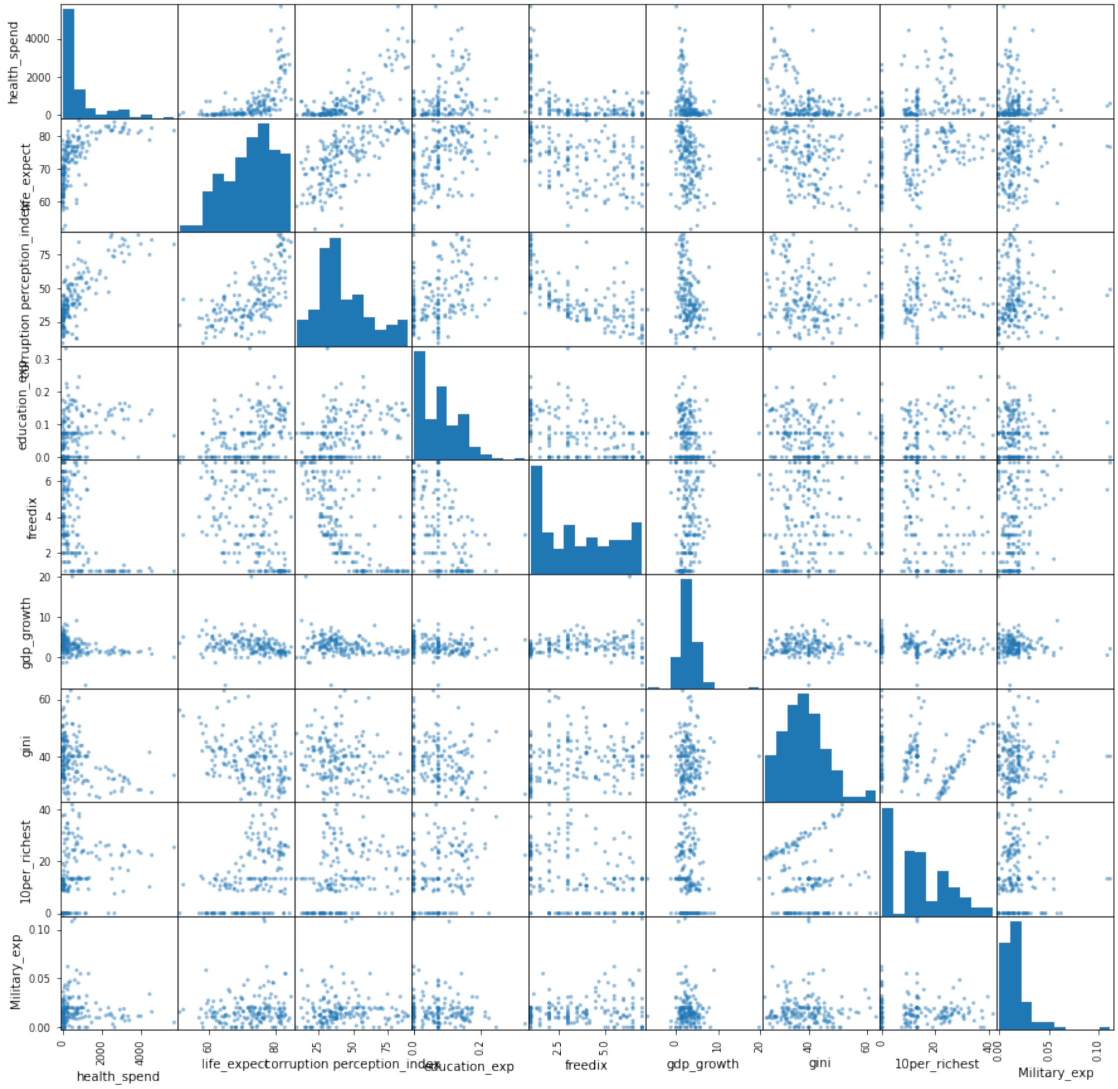
	corruption perception_index	education_exp
health_spend	0.791839	0.305043
life_expect	0.658276	0.401120
corruption perception_index	1.000000	0.343580
education_exp	0.343580	1.000000
freedix	-0.703493	-0.464866

```
gdp_growth                                         -0.267340      -0.142323
gini                                               -0.284537      -0.243498
10per_richest                                       0.313851       0.330067
 Military_exp                                       0.012678      -0.075729

                             freedix  gdp_growth      gini  10per_richest  \
health_spend               -0.532935   -0.323026 -0.373218       0.285947
life_expect                -0.488161   -0.243741 -0.408390       0.467238
corruption perception_index -0.703493   -0.267340 -0.284537       0.313851
education_exp              -0.464866   -0.142323 -0.243498       0.330067
freedix                     1.000000    0.166031  0.158206      -0.358404
gdp_growth                  0.166031    1.000000  0.035650      -0.132602
gini                        0.158206    0.035650  1.000000      -0.084460
10per_richest              -0.358404   -0.132602 -0.084460       1.000000
 Military_exp               0.175848   -0.085912 -0.007761      -0.044415

                             Military_exp
health_spend                    -0.042418
life_expect                      0.118763
corruption perception_index      0.012678
education_exp                   -0.075729
freedix                          0.175848
gdp_growth                      -0.085912
gini                            -0.007761
10per_richest                   -0.044415
 Military_exp                    1.000000
```

[21]:
```
pd.plotting.scatter_matrix(df, figsize=(15,15));
```



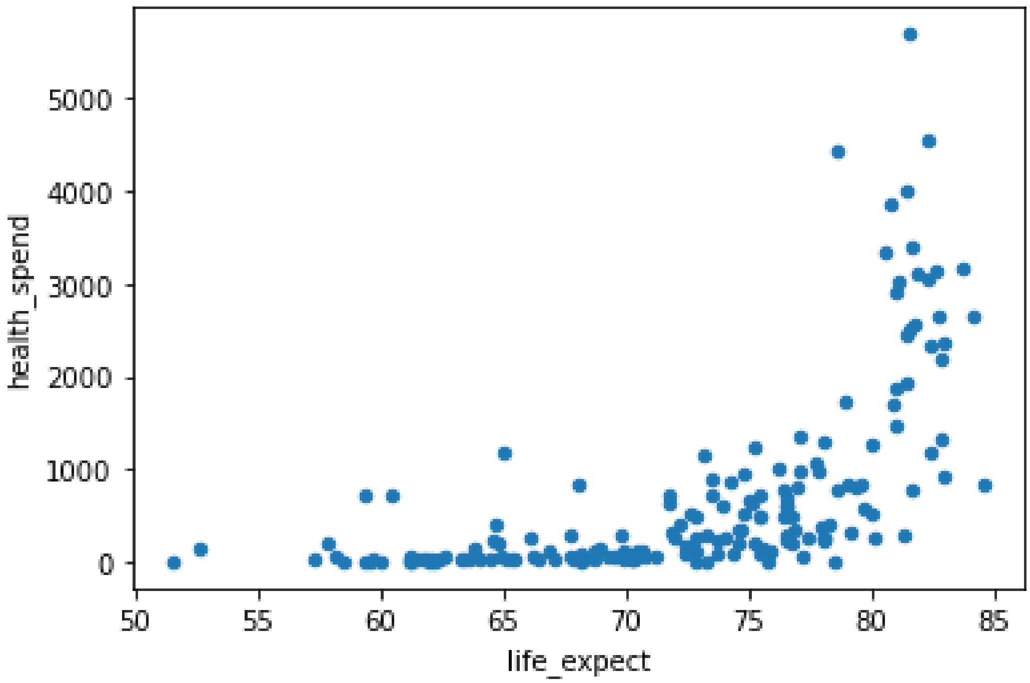
We can observe that **life expectancy** is correlated in a higher level to: health expenditure, corruption, inequality and education than to other variables.

3.1 Is there a direct correlation between goverment expenditure and life expetency?

There are 2 variables that express the goverment expenditure in society. The health expenditure and the education expenditure. Let´s analice them separately

3.1.1 Health expenditure

[56]:
```
df.plot(x= 'life_expect', y='health_spend', kind='scatter');
```



In the scatter plot we can see a clear correlation between our 2 variables, let's explore them in detail

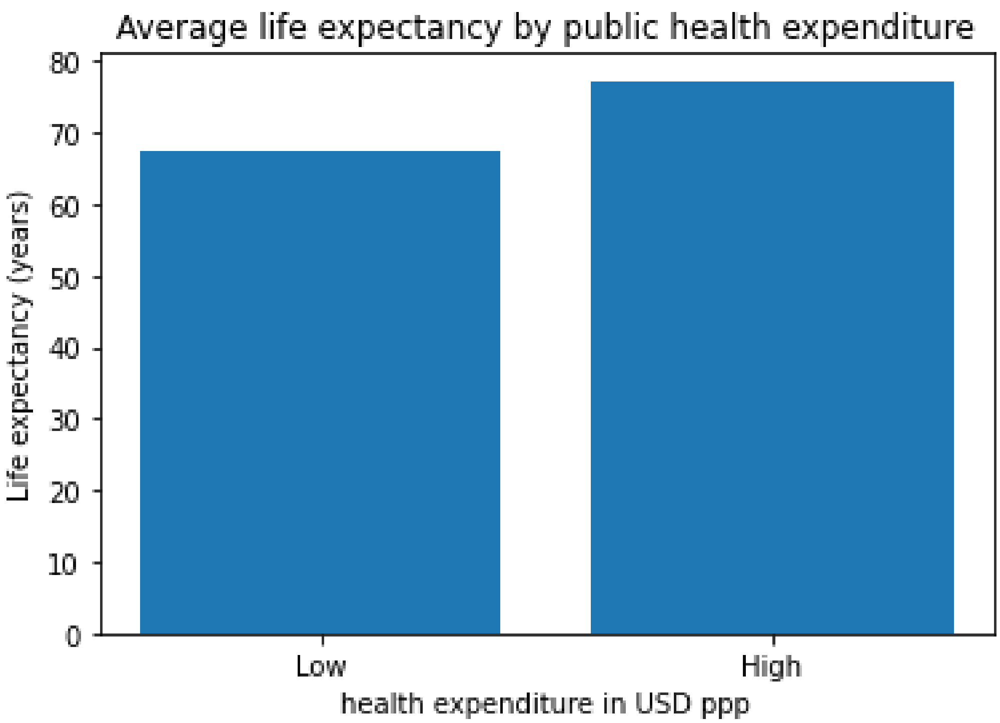
[49]:
```
#Health descrption
print(df['health_spend'].describe())
health_median = df['health_spend'].median()
print('The median of health expenditure is {}'.format(health_median))
```

```
count     177.000000
mean      712.544859
std      1047.657012
min         0.000000
25%        50.300000
50%       260.000000
75%       830.000000
max      5690.000000
Name: health_spend, dtype: float64
The median of health expenditure is 260.0
```

[106]:
```
low_spend = df.query('health_spend < 260')
high_spend = df.query('health_spend >= 260')
locations = [1, 2]
heights = [low_spend.life_expect.mean(), high_spend.life_expect.mean()]
labels = ['Low', 'High']
plt.bar(locations, heights, tick_label=labels);
```

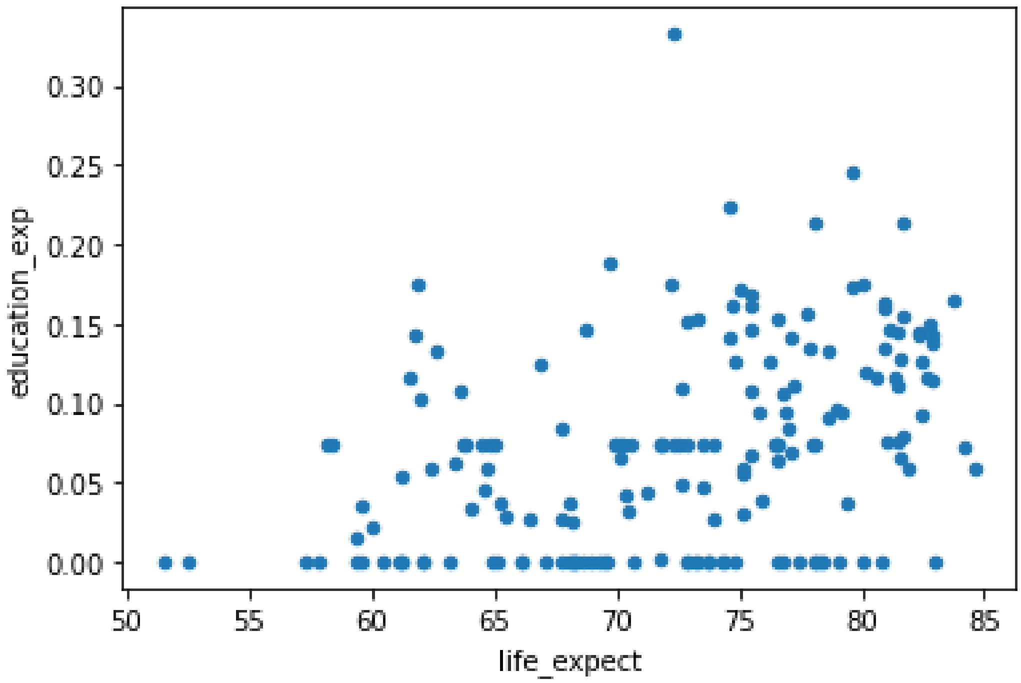
```
plt.title('Average life expectancy by public health expenditure');
plt.xlabel('health expenditure in USD ppp');
plt.ylabel('Life expectancy (years)');
print('The life expectancy of a citizen in a country that spends less than 260␣
↪USD in health care is {}'.format(round(low_spend.life_expect.mean(), 2)))
print('The life expectancy of a citizen in a country that spends more than 260␣
↪USD in health care is {}'.format(round(high_spend.life_expect.mean(),2)))
print('The difference is {} years'.format(round(high_spend.life_expect.mean() -␣
↪low_spend.life_expect.mean(),2)))
```

```
The life expectancy of a citizen in a country that spends less than 260 USD in
health care is 67.62
The life expectancy of a citizen in a country that spends more than 260 USD in
health care is 77.28
The difference is 9.66 years
```



3.1.2 Education expenditure

[70]:
```
df.plot(x= 'life_expect', y='education_exp', kind='scatter');
```



It is not clear that there is a correlation due to some data points, but let's do a deeper investigation of it

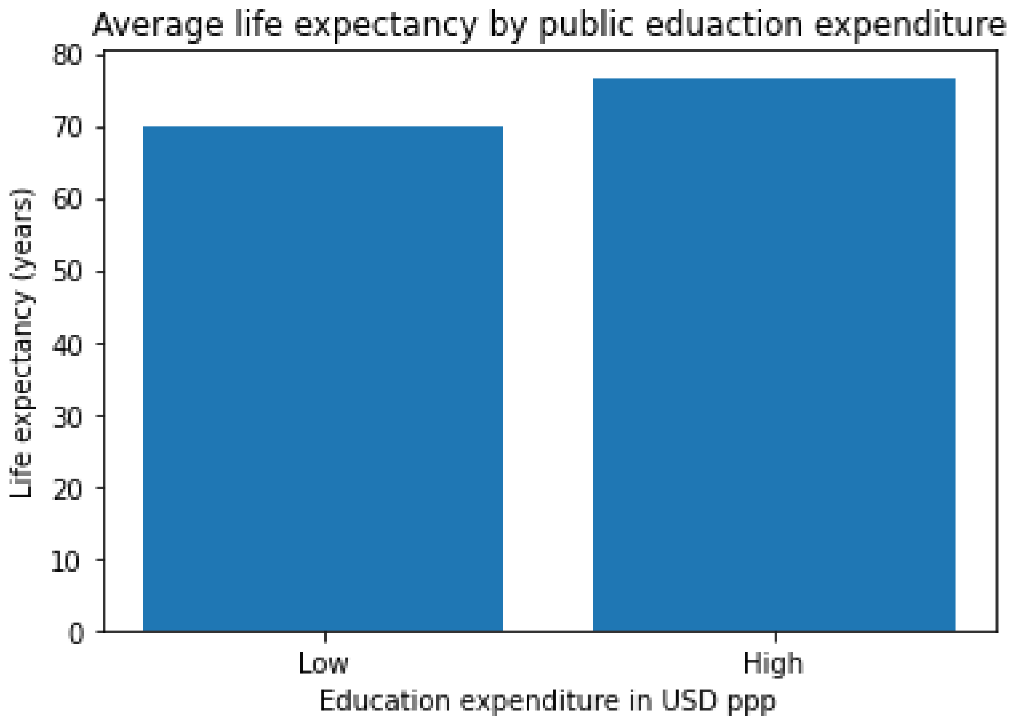
[47]:
```
#Education description
print(df['education_exp'].describe())
edc_median = round(df['education_exp'].median(), 4)
print('The median of education expenditure is {}%'.format((edc_median)*100))
```

```
count    177.000000
mean       0.072323
std        0.063873
min        0.000000
25%        0.000000
50%        0.073333
75%        0.116800
max        0.332667
Name: education_exp, dtype: float64
0.0733
The median of education expenditure is 7.33%
```

[107]:
```
edc_low_spend = df.query('education_exp < 0.074')
edc_high_spend = df.query('education_exp >= 0.074')
locations = [1, 2]
heights = [edc_low_spend.life_expect.mean(), edc_high_spend.life_expect.mean()]
labels = ['Low', 'High']
```

```
plt.bar(locations, heights, tick_label=labels);
plt.title('Average life expectancy by public eduaction expenditure');
plt.xlabel('Education expenditure in USD ppp');
plt.ylabel('Life expectancy (years)');
print('The life expectancy of a citizen in a country that spends less than 7.3%␣
↪of its GDP in primary education is {}'.format(round(edc_low_spend.
↪life_expect.mean(), 2)))
print('The life expectancy of a citizen in a country that spends more than 7.3%␣
↪of its GDP primary education is {}'.format(round(edc_high_spend.life_expect.
↪mean(),2)))
```

```
The life expectancy of a citizen in a country that spends less than 7.3% of its
GDP in primary education is 69.96
The life expectancy of a citizen in a country that spends more than 7.3% of its
GDP primary education is 76.62
```



3.2 Conclusion

[54]:
```
#Here we are merging our expenditure means to calculate a life expectancy by a␣
↪whole goverment expenditure
low_exp_life_mean = round((low_spend.life_expect.mean() + edc_low_spend.
↪life_expect.mean())/2, 2)
```

```
high_exp_life_mean = round((high_spend.life_expect.mean() + edc_high_spend.
 ↪life_expect.mean())/2, 2)
dif_expectancy = round((high_exp_life_mean - low_exp_life_mean), 2)
print('On average a person that lives in a country with low goverment social␣
 ↪expenditure will die at the age of {},\
while a person living in a country that invests in its citizens will live {}.␣
 ↪The difference is {} years'.
      format(low_exp_life_mean, high_exp_life_mean, dif_expectancy))
```

```
On average a person that lives in a country with low goverment social
expenditure will die at the age of 68.79,while a person living in a country that
invests in its citizens will live 76.95. The difference is 8.16 years
```

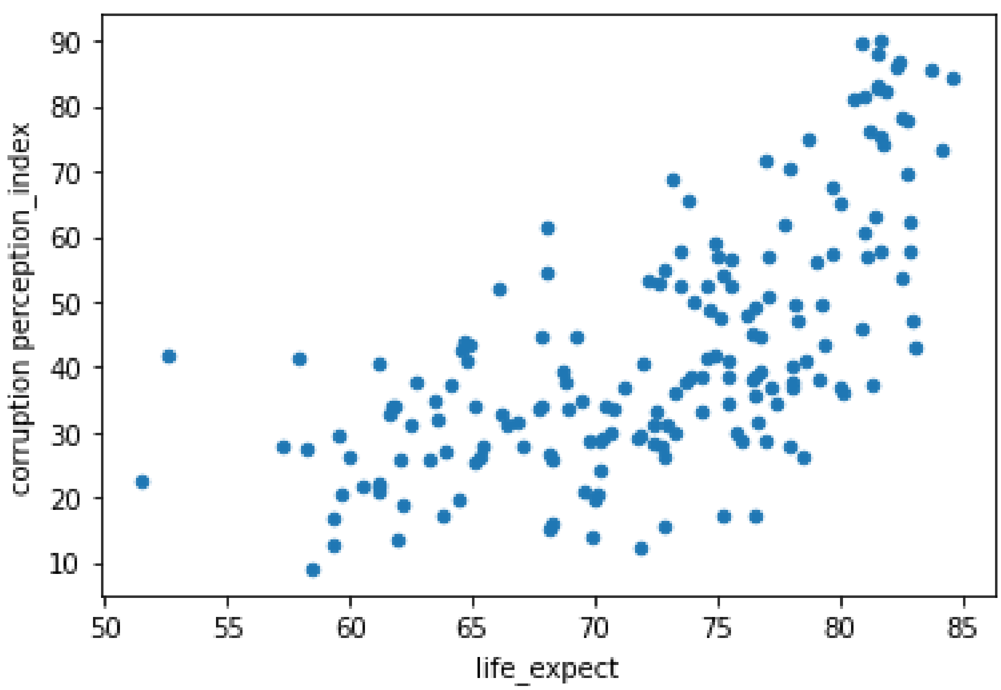
3.3 Do social economic factors such as corruption and inequality affect the life of citizens?

3.3.1 Corruption perception index

For analyze corruption we can group the countries by levels of corruption. Let's do a group by quarters taking the min, 25%, 50%, 75% and Max as the list of values.

[74]:
```
print(df.plot(x= 'life_expect', y='corruption perception_index',␣
 ↪kind='scatter'))
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
```



[59]:
```
df['corruption perception_index'].describe()
```

[59]:
```
count    177.000000
mean      42.611902
std       19.011440
min        9.000000
25%       28.666667
50%       38.000000
75%       53.666667
max       90.000000
Name: corruption perception_index, dtype: float64
```

[78]:
```
#Now to analize corruption, we are going to create categories
# Bin edges that will be used to "cut" the data into groups
bin_edges = [8.9, 28.66, 38, 53.66, 91] # Fill in this list with five values␣
↪you just found
bin_names = ['High', 'Moderately_High', 'Medium', 'Low']
df['corruptions_levels'] = pd.cut(df['corruption perception_index'], bin_edges,␣
↪labels=bin_names)
df.describe()
```

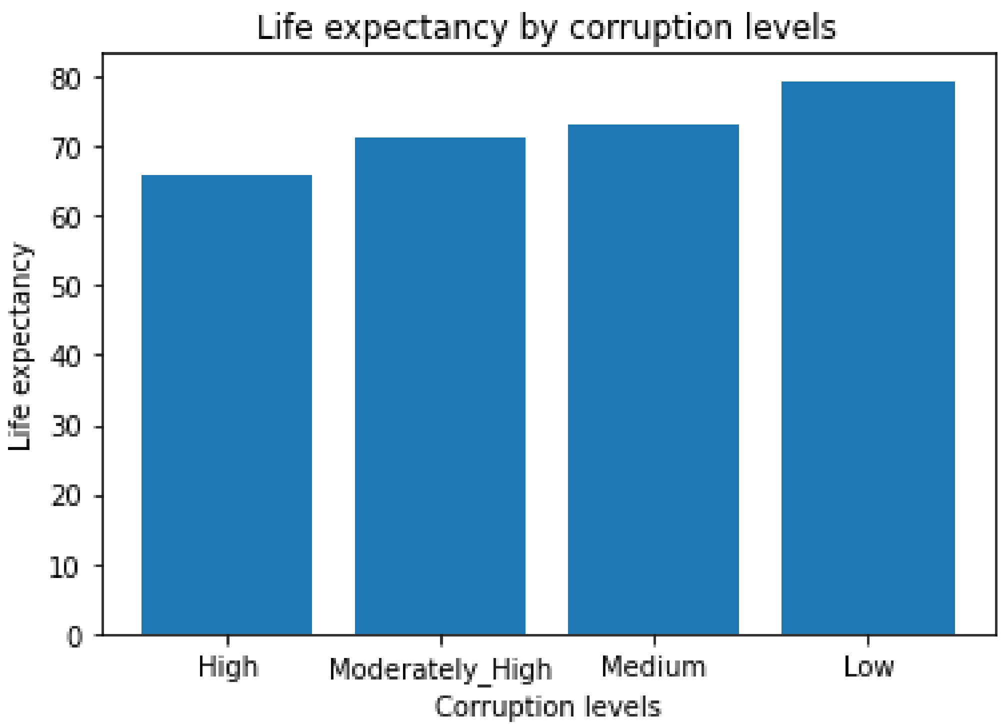
[78]:
```
       health_spend  life_expect  corruption perception_index  education_exp  \
count    177.000000   177.000000                   177.000000     177.000000
mean     712.544859    72.479473                    42.611902       0.072323
std     1047.657012     7.358934                    19.011440       0.063873
min        0.000000    51.500000                     9.000000       0.000000
25%       50.300000    67.700000                    28.666667       0.000000
50%      260.000000    73.533333                    38.000000       0.073333
75%      830.000000    78.100000                    53.666667       0.116800
max     5690.000000    84.633333                    90.000000       0.332667

          freedix  gdp_growth        gini  10per_richest  Military_exp
count  177.000000  177.000000  177.000000     177.000000    177.000000
mean     3.545198    2.929712   38.749153      13.259454      0.017145
std      2.023886    2.313622    7.595394      11.272352      0.015659
min      1.000000   -6.806667   24.933333       0.000000      0.000000
25%      1.666667    1.550000   32.800000       0.000000      0.009327
50%      3.166667    2.630000   38.400000      12.866667      0.014267
75%      5.500000    4.066667   43.200000      22.833333      0.020000
max      7.000000   19.906667   63.033333      41.666667      0.111233
```

[61]:
```
print(df.groupby('corruptions_levels')['life_expect'].mean())
location = [1, 2, 3, 4]
corruption_levels_mean = [65.99, 71.072, 73.1, 79.341]
plt.bar(location, corruption_levels_mean, tick_label=bin_names)
plt.title('Life expectancy by corruption levels')
plt.xlabel('Corruption levels')
```

```
plt.ylabel('Life expectancy');
```

```
corruptions_levels
High                65.994309
Moderately_High     71.072109
Medium              73.100000
Low                 79.341481
Name: life_expect, dtype: float64
```



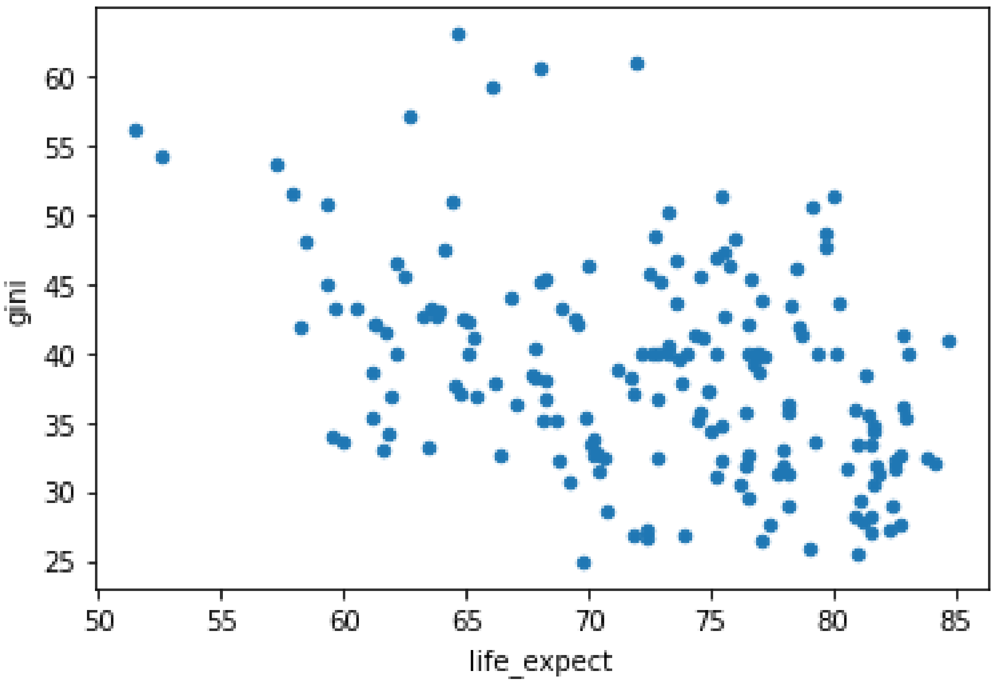
[69]:
```
dif_corruption = round((79.34 - 65.99), 2)
('The diffence between a country with high corruption levels and low corruption␣
 ↪levels could significate {} years of life of a person'.
 ↪format(dif_corruption))
```

[69]:
```
'The diffence between a country with high corruption levels and low corruption
levels could significate 13.35 years of life of a person'
```

3.3.2 Inequality; the gini index

[75]:
```
df.plot(x= 'life_expect', y='gini', kind='scatter')
```

[75]:
```
<AxesSubplot:xlabel='life_expect', ylabel='gini'>
```



[81]:
```
df['gini'].describe()
```

[81]:
```
count    177.000000
mean      38.749153
std        7.595394
min       24.933333
25%       32.800000
50%       38.400000
75%       43.200000
max       63.033333
Name: gini, dtype: float64
```

We are going to create ranges going every 5%, in this way would be clearer for us if some levels of inequality are better than others

[88]:
```
#Now to analize inequality, we are going to create categories
# Bin edges that will be used to "cut" the data into groups
bin_edges = [23,28,33,38,43,48,53,58,63.1] # Fill in this list with five values␣
↪you just found
bin_names = ['1','2', '3', '4','5','6','7','8']
df['inequality_levels'] = pd.cut(df['gini'], bin_edges, labels=bin_names)
```

[98]:
```
print(df.groupby('inequality_levels')['life_expect'].mean())
```

```
inequality_levels
1    77.112821
```

```
2    76.566667
3    72.376923
4    71.668085
5    70.223457
6    71.780000
7    56.008333
8    67.683333
Name: life_expect, dtype: float64
```

[99]:
```
inequality_means = [77.1,  76.5, 72.3, 71.6, 70.22, 71.78,56, 67.68]
location = [1, 2, 3, 4, 5, 6, 7, 8]
plt.bar(location, inequality_means, tick_label=location)
plt.title('Life expectancy by gini index')
plt.xlabel('leves of inequality')
plt.ylabel('Life expectancy');
```

After separating the gini in ranges of 5% we can see a trend but it is not explict, let's take the median and create two groups of "High" and "Low" inequality

[100]:
```
df['gini'].describe()
```

[100]:
```
count    177.000000
mean      38.749153
std        7.595394
```

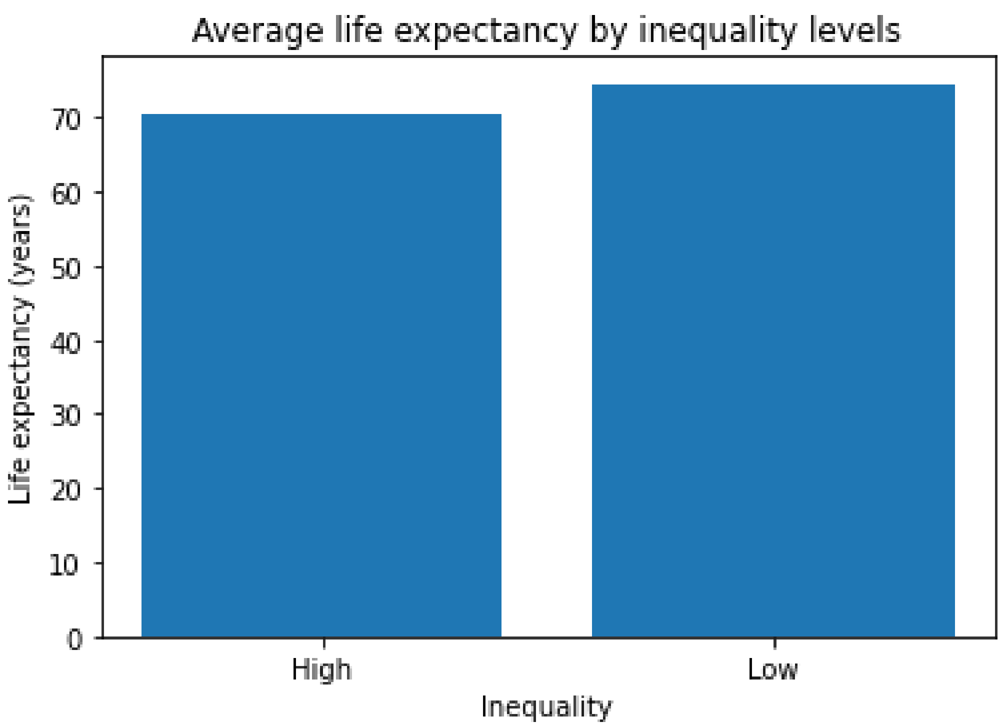
```
min        24.933333
25%        32.800000
50%        38.400000
75%        43.200000
max        63.033333
Name: gini, dtype: float64
```

[103]:

```
high_inequality = df.query('gini >= 38.4')
low_inequality = df.query('gini < 38.4')
locations = [1, 2]
heights = [high_inequality.life_expect.mean(), low_inequality.life_expect.
 ↪mean()]
labels = ['High', 'Low']
plt.bar(locations, heights, tick_label=labels);
plt.title('Average life expectancy by inequality levels');
plt.xlabel('Inequality');
plt.ylabel('Life expectancy (years)');

print('Life expectancy in low inequality countries {}'.
 ↪format(round(low_inequality.life_expect.mean(),2)))
print('Life expectancy in high inequality countries {}'.
 ↪format(round(high_inequality.life_expect.mean(),2)))
```

```
Life expectancy in low inequality countries 74.54
Life expectancy in high inequality countries 70.44
```



After the analysis we can observe the following: -Less corrupt countries lives on average 13.35 years than more corrupt countries. -Countries with higher inequality have a lower life expectancy than countries with less inequality.

4 Final conclusions

Disclaimer This investigation used just 3 years of data and simplify it by making an average result of the 3 ones. So it could no be conclusive on causation.

4.0.1 Wich variables predict longevity?

We can observe that **life expectancy** is correlated in a higher level to: health expenditure, corruption, inequality and education than to other variables. It is not conclusive because the lack of some statistical analysis, but it could be a hint of factors that affects people's years of life

4.0.2 Is there a direct correlation between goverment expenditure and life expetency?

Yes, there is correlation between social expenditure and the years of life of the country's population.

Health expenditure: A country with higher healthcare expenditure has 9.66 more years of life expectancy than those with a worse health system. **Eduacition expenditure:** The life expectancy of a citizen in a country that spends less than 7.3% of its GDP in primary education is 69.96 The life expectancy of a citizen in a country that spends more than 7.3% of its GDP primary education is 76.62

Public expenditure On average a person that lives in a country with low goverment social expenditure will die at the age of 68.79,while a person living in a country that invests in its citizens will live 76.95. The difference is 8.16 years

4.0.3 Do social economic factors such as inequality and corruption affect the life of citizens?

Yes, those 2 variables are correlated to life expectancy. **Corruption:** The difference between a country with high corruption levels and low corruption levels could significate 13.35 years of life of a person **Inequality:** While the life expectancy in a country with low inequality levels is 74.54, the life expectancy in high inequality countries 70.44

###Bibliografy: https://stackoverflow.com/questions/64455605/python-spyder-show-all-colums-of-a-pandas-dataframe-in-describe https://eprints.ucm.es/id/eprint/48304/1/ManualJupyter.pdf Udacity classes https://matplotlib.org/api/pyplot_api.html#matplotlib.pyplot.plot