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CSE

CS 550 ASSIGNMENT_1_PARTB

Part 2: Life Expectancy (WHO)

Life expectancy is the number of years that an individual is expected to live as determined by statistics. It is the age to which an average person is expected to live, based on the person's sex, health factors, and other demographic data.Population ageing has become an important developmental issue that requires urgent action.

Problem Statement

Part 2: Life Expectancy (WHO)

Objectives

The data was collected from WHO and the United Nations website. The objective of this practice is to

A. Feature Selection: Do various predicting factors which have been chosen initially really affect the Life expectancy? What are the predicting variables actually affecting life expectancy?

B. Should a country having a lower life expectancy value (<65) increase its healthcare expenditure in order to improve its average lifespan?

C. How do Infant and Adult mortality rates affect life expectancy?

D. Does Life Expectancy have positive or negative correlation with eating habits, lifestyle, exercise, smoking, drinking alcohol etc.

E. What is the impact of schooling on the lifespan of humans? F. Does Life Expectancy have a positive or negative relationship with drinking alcohol?

G. Do densely populated countries tend to have lower life expectancy?

H. What is the impact of Immunization coverage on life Expectancy?

(Kaggle:https://www.kaggle.com/datasets/kumarajarshi/life-expectancywho?select=Life+Expectancy+Data.csv)

Importing Libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas.util.testing as tm
import matplotlib.pyplot as plt
import seaborn as sns
pd.set_option('display.max_columns', None)
from sklearn import preprocessing
import tensorflow as tf
from tensorflow import feature_column
from tensorflow.keras import layers
from sklearn.model_selection import train_test_split
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: FutureWarning: pandas.util.testing is deprecated. Use the functions in the public API at pandas.testing instead.
  """
```

Reading data

In [2]:

```
df = pd.read_csv("Life Expectancy Data.csv")
df
```

Out[2]:

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	under-five deaths	Polio	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Income composition of resources	Schooling
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	65.0	1154	19.1	83	6.0	8.16	65.0	0.1	584.259210	33736494.0	17.2	17.3	0.479	10.1
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582	62.0	492	18.6	86	58.0	8.18	62.0	0.1	612.696514	327582.0	17.5	17.5	0.476	10.0
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243	64.0	430	18.1	89	62.0	8.13	64.0	0.1	631.744976	31731688.0	17.7	17.7	0.470	9.9
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215	67.0	2787	17.6	93	67.0	8.52	67.0	0.1	669.959000	3696958.0	17.9	18.0	0.463	9.8
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109	68.0	3013	17.2	97	68.0	7.87	68.0	0.1	63.537231	2978599.0	18.2	18.2	0.454	9.5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2933	Zimbabwe	2004	Developing	44.3	723.0	27	4.36	0.000000	68.0	31	27.1	42	67.0	7.13	65.0	33.6	454.366654	12777511.0	9.4	9.4	0.407	9.2
2934	Zimbabwe	2003	Developing	44.5	715.0	26	4.06	0.000000	7.0	998	26.7	41	7.0	6.52	68.0	36.7	453.351155	12633897.0	9.8	9.9	0.418	9.5
2935	Zimbabwe	2002	Developing	44.8	73.0	25	4.43	0.000000	73.0	304	26.3	40	73.0	6.53	71.0	39.8	57.348340	125525.0	1.2	1.3	0.427	10.0
2936	Zimbabwe	2001	Developing	45.3	686.0	25	1.72	0.000000	76.0	529	25.9	39	76.0	6.16	75.0	42.1	548.587312	12366165.0	1.6	1.7	0.427	9.8
2937	Zimbabwe	2000	Developing	46.0	665.0	24	1.68	0.000000	79.0	1483	25.5	39	78.0	7.10	78.0	43.5	547.358878	12222251.0	11.0	11.2	0.434	9.8

2938 rows × 22 columns

In [3]:

```
tran=df
```

Visualizing the data

In [4]:

```
# number of rows and columns
df.shape
```

Out[4]:

```
(2938, 22)
```

In [5]:

```
# preview first 5 rows
df.head()
```

Out[5]:

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	under-five deaths	Polio	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Income composition of resources	Schooling
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	65.0	1154	19.1	83	6.0	8.16	65.0	0.1	584.259210	33736494.0	17.2	17.3	0.479	10.1
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582	62.0	492	18.6	86	58.0	8.18	62.0	0.1	612.696514	327582.0	17.5	17.5	0.476	10.0
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243	64.0	430	18.1	89	62.0	8.13	64.0	0.1	631.744976	31731688.0	17.7	17.7	0.470	9.9
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215	67.0	2787	17.6	93	67.0	8.52	67.0	0.1	669.959000	3696958.0	17.9	18.0	0.463	9.8
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109	68.0	3013	17.2	97	68.0	7.87	68.0	0.1	63.537231	2978599.0	18.2	18.2	0.454	9.5

In [6]:

```
# preview last 5 rows
```

```
# preview last 5 rows
df.tail()
```

Out[6]:

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles	BMI	under-five deaths	Polio	Total expenditure	Diphtheria	HIV/AIDS	GDP	Population	thinness 1-19 years	thinness 5-9 years	Income composition of resources	Schooling
2933	Zimbabwe	2004	Developing	44.3	723.0	27	4.36	0.0	68.0	31	27.1	42	67.0	7.13	65.0	33.6	454.366654	12777511.0	9.4	9.4	0.407	9.2
2934	Zimbabwe	2003	Developing	44.5	715.0	26	4.06	0.0	7.0	998	26.7	41	7.0	6.52	68.0	36.7	453.351155	12633897.0	9.8	9.9	0.418	9.5
2935	Zimbabwe	2002	Developing	44.8	73.0	25	4.43	0.0	73.0	304	26.3	40	73.0	6.53	71.0	39.8	57.348340	125525.0	1.2	1.3	0.427	10.0
2936	Zimbabwe	2001	Developing	45.3	686.0	25	1.72	0.0	76.0	529	25.9	39	76.0	6.16	75.0	42.1	548.587312	12366165.0	1.6	1.7	0.427	9.8
2937	Zimbabwe	2000	Developing	46.0	665.0	24	1.68	0.0	79.0	1483	25.5	39	78.0	7.10	78.0	43.5	547.358878	12222251.0	11.0	11.2	0.434	9.8

In [7]:

```
# traning the datatype of each column
df.dtypes
```

Out[7]:

```
Country                             object
Year                                 int64
Status                              object
Life expectancy                    float64
Adult Mortality                    float64
infant deaths                        int64
Alcohol                            float64
percentage expenditure             float64
Hepatitis B                        float64
Measles                              int64
 BMI                               float64
under-five deaths                    int64
Polio                              float64
Total expenditure                  float64
Diphtheria                         float64
 HIV/AIDS                          float64
GDP                                float64
Population                         float64
 thinness  1-19 years              float64
 thinness 5-9 years                float64
Income composition of resources    float64
Schooling                          float64
dtype: object
```

Data Cleaning and Visualization

Standardising column names

In [8]:

```
# fixing messy column names
df.columns = df.columns.str.strip().str.lower().str.replace(' ', '_').str.replace('(', '').str.replace(')', '')

# preview column names to see changes made
print(df.columns)
```

```
Index(['country', 'year', 'status', 'life_expectancy', 'adult_mortality',
       'infant_deaths', 'alcohol', 'percentage_expenditure', 'hepatitis_b',
       'measles', 'bmi', 'under-five_deaths', 'polio', 'total_expenditure',
       'diphtheria', 'hiv/aids', 'gdp', 'population', 'thinness__1-19_years',
       'thinness_5-9_years', 'income_composition_of_resources', 'schooling'],
      dtype='object')
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: FutureWarning: The default value of regex will change from True to False in a future version. In addition, single character r
egular expressions will *not* be treated as literal strings when regex=True.
```

Duplicated entries

In [9]:

```
# tran for duplicated rows
df.duplicated().sum()

# none found
```

Out[9]:

```
0
```

Null Values

In [10]:

```
# tran for null values
df.isnull().sum()
```

Out[10]:

```
country                              0
year                                 0
status                               0
life_expectancy                     10
adult_mortality                     10
infant_deaths                        0
alcohol                            194
percentage_expenditure               0
hepatitis_b                        553
measles                              0
bmi                                 34
under-five_deaths                    0
polio                               19
total_expenditure                  226
diphtheria                          19
hiv/aids                             0
gdp                                448
population                         652
thinness__1-19_years                34
thinness_5-9_years                  34
income_composition_of_resources    167
schooling                          163
dtype: int64
```

In [11]:

```
# select a list of all countries from the country column
country_list = df.country.unique()

# create a list of the other columns with null values that need to be interpolated
interpolate_list =['life_expectancy', 'adult_mortality', 'infant_deaths', 'alcohol',
                   'percentage_expenditure', 'hepatitis_b', 'measles', 'bmi', 'under-five_deaths',
                   'polio', 'total_expenditure', 'diphtheria', 'hiv/aids', 'gdp', 'population',
                   'thinness__1-19_years', 'thinness_5-9_years', 'income_composition_of_resources',
                   'schooling']

# interpolate the different columns for each country separately
for country in country_list:
    df.loc[df['country'] == country,interpolate_list] = df.loc[df['country'] == country,interpolate_list].interpolate()
```

In [12]:

```
# drop the remaining null values
df.dropna(inplace=True)
df
```

Out[12]:

	country	year	status	life_expectancy	adult_mortality	infant_deaths	alcohol	percentage_expenditure	hepatitis_b	measles	bmi	under-five_deaths	polio	total_expenditure	diphtheria	hiv/aids	gdp	population	thinness__1-19_years	thinness_5-9_years	income_com
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	65.0	1154	19.1	83	6.0	8.16	65.0	0.1	584.259210	33736494.0	17.2	17.3	
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582	62.0	492	18.6	86	58.0	8.18	62.0	0.1	612.696514	327582.0	17.5	17.5	
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243	64.0	430	18.1	89	62.0	8.13	64.0	0.1	631.744976	31731688.0	17.7	17.7	
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215	67.0	2787	17.6	93	67.0	8.52	67.0	0.1	669.959000	3696958.0	17.9	18.0	
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109	68.0	3013	17.2	97	68.0	7.87	68.0	0.1	63.537231	2978599.0	18.2	18.2	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
2933	Zimbabwe	2004	Developing	44.3	723.0	27	4.36	0.000000	68.0	31	27.1	42	67.0	7.13	65.0	33.6	454.366654	12777511.0	9.4	9.4	
2934	Zimbabwe	2003	Developing	44.5	715.0	26	4.06	0.000000	7.0	998	26.7	41	7.0	6.52	68.0	36.7	453.351155	12633897.0	9.8	9.9	
2935	Zimbabwe	2002	Developing	44.8	73.0	25	4.43	0.000000	73.0	304	26.3	40	73.0	6.53	71.0	39.8	57.348340	125525.0	1.2	1.3	
2936	Zimbabwe	2001	Developing	45.3	686.0	25	1.72	0.000000	76.0	529	25.9	39	76.0	6.16	75.0	42.1	548.587312	12366165.0	1.6	1.7	
2937	Zimbabwe	2000	Developing	46.0	665.0	24	1.68	0.000000	79.0	1483	25.5	39	78.0	7.10	78.0	43.5	547.358878	12222251.0	11.0	11.2	

1987 rows × 22 columns

In [13]:

```
#Exporting the already cleaned dataset
df1=df.copy()
df1.to_csv('cleaned.csv')
```

Outliers

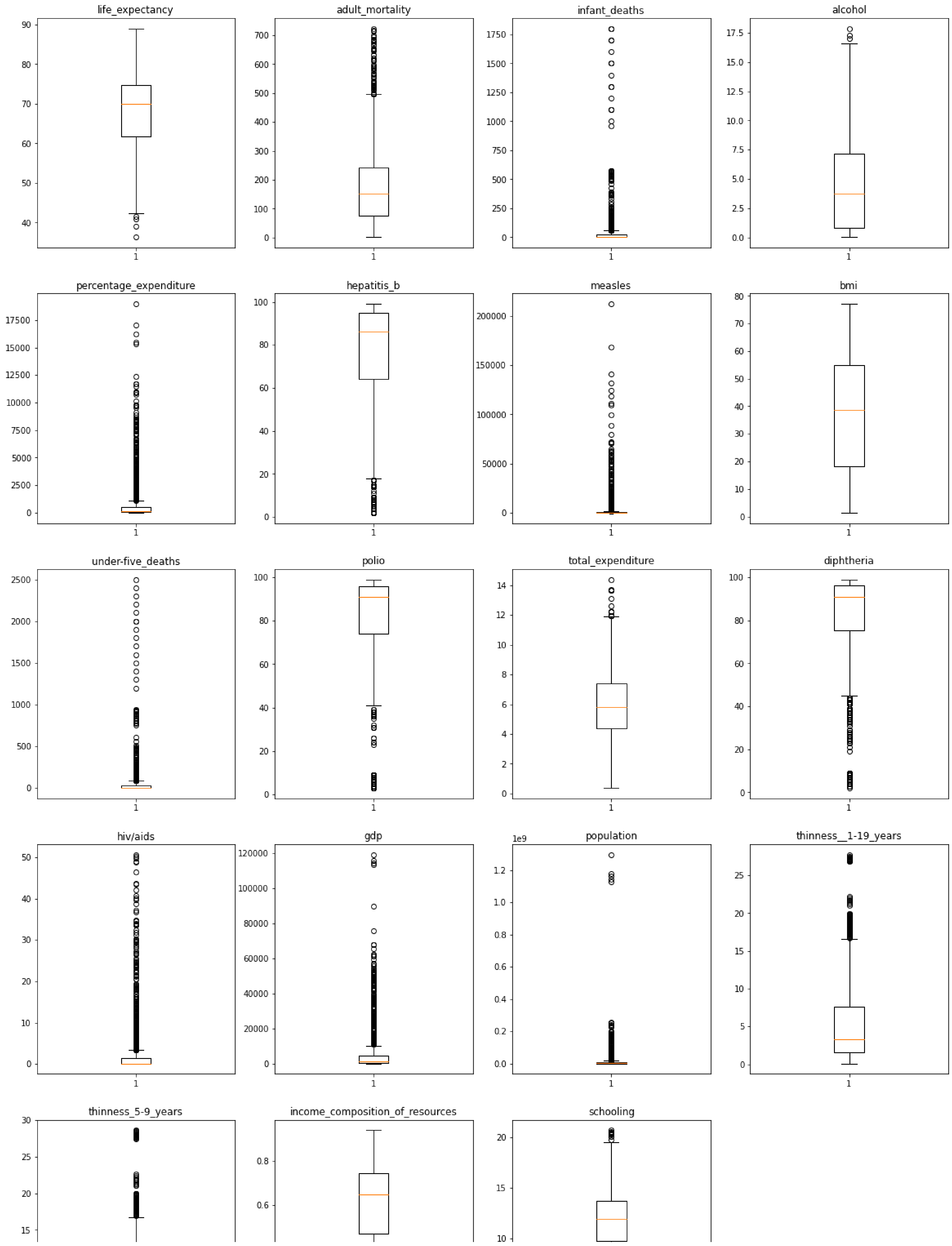
In [14]:

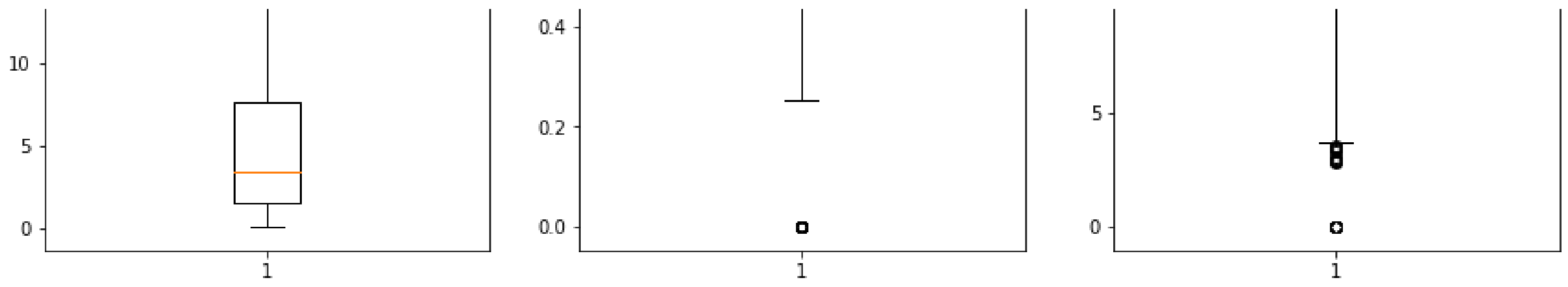
```
# save the column names onto a dictionary
columns_dict={'life_expectancy': 1, 'adult_mortality': 2, 'infant_deaths': 3, 'alcohol': 4,
              'percentage_expenditure': 5, 'hepatitis_b': 6, 'measles': 7, 'bmi': 8, 'under-five_deaths': 9,
              'polio': 10, 'total_expenditure': 11, 'diphtheria': 12, 'hiv/aids': 13, 'gdp': 14, 'population': 15,
              'thinness__1-19_years': 16, 'thinness_5-9_years': 17, 'income_composition_of_resources': 18,
              'schooling': 19}

plt.figure(figsize=(20,30))

# make a boxplot for each numerical column
for variable,i in columns_dict.items():
  plt.subplot(5,4,i)
  plt.boxplot(df[variable])
  plt.title(variable)

plt.show()
```





Anomalies

In [15]:

```
# traning for anomalies

# find quartile ranges for the column sum of bluecars_taken
q1_life_e = df['life_expectancy'].quantile(.25)
q3_life_e = df['life_expectancy'].quantile(.75)

# calculating inter-quartile range using values from above
iqr_life_e = q3_life_e - q1_life_e

# another way is to find quantiles using the percentiles from the numpy library
q1_l_e, q3_l_e = np.percentile(df['life_expectancy'], [25, 75])
# IQR
iqr_l_e = q3_l_e - q1_l_e

# compare if the two values are similar
print(iqr_life_e, iqr_l_e)
```

```
13.0 13.0
```

B. Data Scaling

In [16]:

```
df.columns
```

Out[16]:

```
Index(['country', 'year', 'status', 'life_expectancy', 'adult_mortality',
       'infant_deaths', 'alcohol', 'percentage_expenditure', 'hepatitis_b',
       'measles', 'bmi', 'under-five_deaths', 'polio', 'total_expenditure',
       'diphtheria', 'hiv/aids', 'gdp', 'population', 'thinness__1-19_years',
       'thinness_5-9_years', 'income_composition_of_resources', 'schooling'],
      dtype='object')
```

In [17]:

```
from sklearn.preprocessing import StandardScaler
scalar=StandardScaler()
train=df
train2=train
train2["life_expectancy"]=scalar.fit_transform(train[["life_expectancy"]])
train2["adult_mortality"]=scalar.fit_transform(train[["adult_mortality"]])
train2["infant_deaths"]=scalar.fit_transform(train[["infant_deaths"]])
train2["alcohol"]=scalar.fit_transform(train[["alcohol"]])
train2['measles']=scalar.fit_transform(train[['measles']])
train2["gdp"]=scalar.fit_transform(train[["gdp"]])
train2["population"]=scalar.fit_transform(train[["population"]])
```

In [18]:

```
train2.head(10)
```

Out[18]:

	country	year	status	life_expectancy	adult_mortality	infant_deaths	alcohol	percentage_expenditure	hepatitis_b	measles	bmi	under-five_deaths	polio	total_expenditure	diphtheria	hiv/aids	gdp	population	thinness__1-19_years	thinness_5-9_years	income_composi
0	Afghanistan	2015	Developing	-0.307275	0.667352	0.182893	-1.118195	71.279624	65.0	-0.130219	19.1	83	6.0	8.16	65.0	0.1	-0.418898	0.310590	17.2	17.3	
1	Afghanistan	2014	Developing	-0.832833	0.728150	0.197308	-1.118195	73.523582	62.0	-0.184932	18.6	86	58.0	8.18	62.0	0.1	-0.416420	-0.204305	17.5	17.5	
2	Afghanistan	2013	Developing	-0.832833	0.705351	0.211722	-1.118195	73.219243	64.0	-0.190057	18.1	89	62.0	8.13	64.0	0.1	-0.414761	0.279692	17.7	17.7	
3	Afghanistan	2012	Developing	-0.874054	0.735750	0.233344	-1.118195	78.184215	67.0	0.004747	17.6	93	67.0	8.52	67.0	0.1	-0.411431	-0.152377	17.9	18.0	
4	Afghanistan	2011	Developing	-0.904969	0.758549	0.247758	-1.118195	7.097109	68.0	0.023426	17.2	97	68.0	7.87	68.0	0.1	-0.464265	-0.163448	18.2	18.2	
5	Afghanistan	2010	Developing	-0.946189	0.788948	0.269380	-1.118195	79.679367	66.0	-0.061207	16.7	102	66.0	9.20	66.0	0.1	-0.421593	-0.164919	18.4	18.4	
6	Afghanistan	2009	Developing	-0.966799	0.804147	0.291001	-1.118195	56.762217	63.0	0.010863	16.2	106	63.0	9.42	63.0	0.1	-0.430953	-0.204972	18.6	18.7	
7	Afghanistan	2008	Developing	-1.018325	0.849746	0.312623	-1.113164	25.873925	64.0	-0.093440	15.7	110	64.0	8.33	64.0	0.1	-0.437272	-0.167288	18.8	18.9	
8	Afghanistan	2007	Developing	-1.080155	0.910543	0.327037	-1.115680	10.910156	63.0	-0.131293	15.2	113	63.0	6.73	63.0	0.1	-0.437579	0.200862	19.0	19.1	
9	Afghanistan	2006	Developing	-1.100765	0.910543	0.341452	-1.113164	17.171518	64.0	-0.061124	14.7	116	58.0	7.43	58.0	0.1	-0.446054	-0.169447	19.2	19.3	

In [19]:

```
train3 = pd.DataFrame(train2)
corr = train3.corr()
corr.style.background_gradient(cmap ='coolwarm')
```

Out[19]:

	year	life_expectancy	adult_mortality	infant_deaths	alcohol	percentage_expenditure	hepatitis_b	measles	bmi	under-five_deaths	polio	total_expenditure	diphtheria	hiv/aids	gdp	population	thinness__1-19_years	thinness_ 9_yea
year	1.000000	0.171485	-0.072108	-0.037601	-0.046859	0.089096	0.247259	-0.099554	0.096059	-0.042479	0.117642	0.074139	0.166006	-0.142581	0.119355	0.022775	-0.047477	-0.05348
life_expectancy	0.171485	1.000000	-0.660529	-0.160922	0.392617	0.413683	0.249625	-0.138133	0.599572	-0.187438	0.415188	0.199288	0.442943	-0.576373	0.443612	-0.010840	-0.458724	-0.45009
adult_mortality	-0.072108	-0.660529	1.000000	0.038304	-0.181469	-0.242438	-0.103382	-0.007269	-0.372519	0.052865	-0.208006	-0.096727	-0.210136	0.536273	-0.256955	-0.022403	0.278842	0.28458
infant_deaths	-0.037601	-0.160922	0.038304	1.000000	-0.104406	-0.089772	-0.216949	0.509747	-0.227769	0.996729	-0.152153	-0.147961	-0.156470	0.001739	-0.097720	0.562805	0.481580	0.48759
alcohol	-0.046859	0.392617	-0.181469	-0.104406	1.000000	0.430835	0.106383	-0.029252	0.379327	-0.099713	0.239854	0.227108	0.245454	-0.033756	0.458112	-0.025556	-0.398731	-0.38708
percentage_expenditure	0.089096	0.413683	-0.242438	-0.089772	0.430835	1.000000	-0.011530	-0.069316	0.277788	-0.092480	0.162606	0.217103	0.168910	-0.109680	0.963177	-0.016607	-0.268347	-0.26813
hepatitis_b	0.247259	0.249625	-0.103382	-0.216949	0.106383	-0.011530	1.000000	-0.142059	0.198627	-0.226512	0.451299	0.130435	0.552732	-0.104034	0.009077	-0.092418	-0.166903	-0.18110
measles	-0.099554	-0.138133	-0.007269	0.509747	-0.029252	-0.069316	-0.142059	1.000000	-0.168172	0.519173	-0.113574	-0.111638	-0.119828	0.019600	-0.073858	0.269840	0.227961	0.22332
bmi	0.096059	0.599572	-0.372519	-0.227769	0.379327	0.277788	0.198627	-0.168172	1.000000	-0.238155	0.264753	0.233643	0.266601	-0.239171	0.300517	-0.071306	-0.560982	-0.56794
under-five_deaths	-0.042479	-0.187438	0.052865	0.996729	-0.099713	-0.092480	-0.226512	0.519173	-0.238155	1.000000	-0.169989	-0.148325	-0.177302	0.013390	-0.101404	0.548761	0.483954	0.48875
polio	0.117642	0.415188	-0.208006	-0.152153	0.239854	0.162606	0.451299	-0.113574	0.264753	-0.169989	1.000000	0.153724	0.680436	-0.132156	0.188618	-0.026926	-0.204346	-0.20551
total_expenditure	0.074139	0.199288	-0.096727	-0.147961	0.227108	0.217103	0.130435	-0.111638	0.233643	-0.148325	0.153724	1.000000	0.166398	0.025389	0.211375	-0.078289	-0.233957	-0.24930
diphtheria	0.166006	0.442943	-0.210136	-0.156470	0.245454	0.168910	0.552732	-0.119828	0.266601	-0.177302	0.680436	0.166398	1.000000	-0.142735	0.190969	-0.022151	-0.223845	-0.21465

hiv/aids	year	life_expectancy	adult_mortality	infant_deaths	alcohol	percentage_expenditure	hepatitis_b	measles	bmi	under-five_deaths	polio	total_expenditure	diphtheria	hiv/aids	gdp	population	thinness__1-19_years	thinness_
	0.142581	-0.576373	0.536273	0.001739	0.033756	-0.109680	-0.104034	0.019600	0.239171	[illegible]	0.132156	0.025389	-0.142735	1.000000	0.121314	-0.032315	[illegible]	[illegible]
gdp	0.119355	0.443612	-0.256955	-0.097720	0.458112	0.963177	0.009077	-0.073858	0.300517	-0.101404	0.188618	0.211375	0.190969	-0.121314	1.000000	-0.019751	-0.288131	-0.28787
population	0.022775	-0.010840	-0.022403	0.562805	-0.025556	-0.016607	-0.092418	0.269840	-0.071306	0.548761	-0.026926	-0.078289	-0.022151	-0.032315	-0.019751	1.000000	0.259960	0.25756
thinness__1-19_years	-0.047477	-0.458724	0.278842	0.481580	-0.398731	-0.268347	-0.166903	0.227961	-0.560982	0.483954	-0.204346	-0.233957	-0.223845	0.193041	-0.288131	0.259960	1.000000	0.92687
thinness_5-9_years	-0.053483	-0.450095	0.284581	0.487596	-0.387087	-0.268131	-0.181161	0.223325	-0.567943	0.488759	-0.205516	-0.249369	-0.214652	0.195961	-0.287875	0.257564	0.926872	1.00000
income_composition_of_resources	0.242900	0.726753	-0.411010	-0.137175	0.532173	0.408174	0.239386	-0.137648	0.539862	-0.157039	0.395265	0.194385	0.436006	-0.242581	0.450799	0.001611	-0.432073	-0.41420
schooling	0.225046	0.744703	-0.404160	-0.195815	0.590261	0.426801	0.268951	-0.146625	0.584998	-0.212678	0.437793	0.256340	0.458794	-0.209940	0.468299	-0.024767	-0.464851	-0.44897

Exploratory Data Analysis

In [20]:

```
df.describe()
```

Out[20]:

	year	life_expectancy	adult_mortality	infant_deaths	alcohol	percentage_expenditure	hepatitis_b	measles	bmi	under-five_deaths	polio	total_expenditure	diphtheria	hiv/aids	gdp	population	thinness__1-19_years	thinn
count	1987.000000	1.987000e+03	1.987000e+03	1.987000e+03	1.987000e+03	1987.000000	1987.00000	1.987000e+03	1987.000000	1987.000000	1987.000000	1987.000000	1987.000000	1987.000000	1.987000e+03	1.987000e+03	1987.000000	1987
mean	2006.984902	9.225970e-16	1.430383e-17	-1.430383e-17	7.151915e-18	685.492318	73.86160	-3.575957e-18	36.428636	50.932562	80.371917	5.902728	80.454454	2.274937	2.860766e-17	-1.430383e-17	5.129995	5.
std	4.323147	1.000252e+00	1.000252e+00	1.000252e+00	1.000252e+00	1761.669050	29.02807	1.000252e+00	19.736138	188.933117	24.363376	2.287467	24.450153	6.005112	1.000252e+00	1.000252e+00	4.750149	4.
min	2000.000000	-3.264831e+00	-1.323774e+00	-2.639536e-01	-1.118195e+00	0.000000	2.00000	-2.255958e-01	1.400000	0.000000	3.000000	0.370000	2.000000	0.100000	-4.696542e-01	-2.093536e-01	0.100000	0.
25%	2003.000000	-6.473422e-01	-7.613947e-01	-2.567464e-01	-9.119437e-01	29.469887	64.00000	-2.255958e-01	18.150000	1.000000	74.000000	4.360000	75.500000	0.100000	-4.362970e-01	-2.063219e-01	1.600000	1.
50%	2007.000000	1.976738e-01	-1.686166e-01	-2.351247e-01	-1.724573e-01	104.314473	86.00000	-2.239429e-01	38.700000	4.000000	91.000000	5.800000	91.000000	0.100000	-3.535208e-01	-1.878258e-01	3.300000	3.
75%	2011.000000	6.923173e-01	5.153581e-01	-8.377336e-02	6.877615e-01	470.870122	95.00000	-1.843126e-01	55.000000	36.000000	96.000000	7.385000	96.000000	1.400000	-8.283774e-02	-9.182404e-02	7.600000	7.
max	2015.000000	2.165943e+00	4.163223e+00	1.270902e+01	3.374059e+00	18961.348600	99.00000	1.731114e+01	77.100000	2500.000000	99.000000	14.390000	99.000000	50.600000	9.912980e+00	1.973152e+01	27.700000	28.

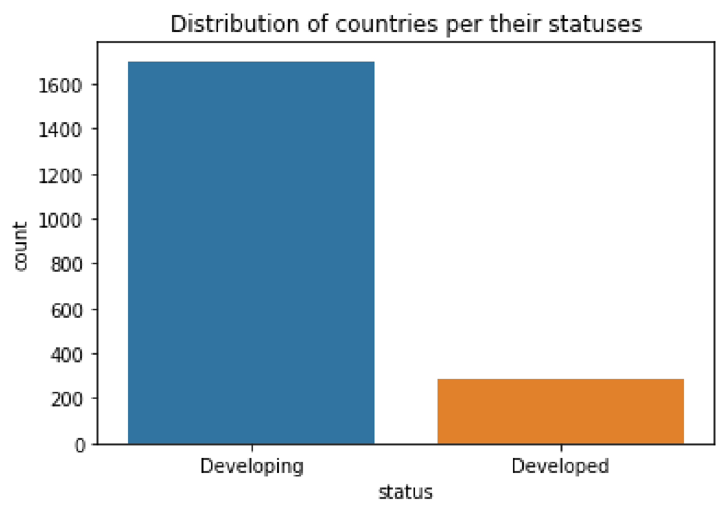
In [21]:

```
#Histogram of the status of different countries
ax = sns.countplot(df['status'], order = df['status'].value_counts().index)
plt.title('Distribution of countries per their statuses')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[21]:

```
Text(0.5, 1.0, 'Distribution of countries per their statuses')
```



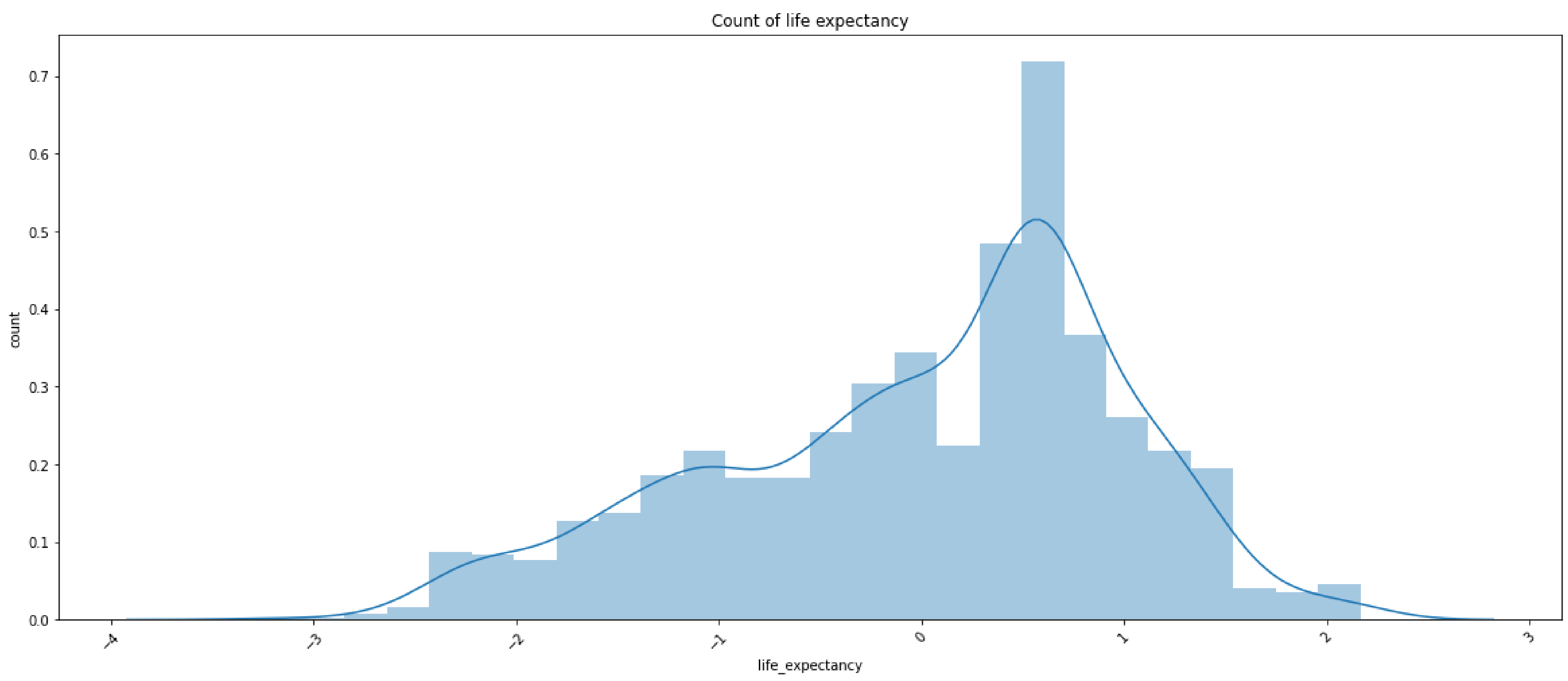
In [22]:

```
#Histogram of the life_expectancy of different countries
plt.figure(figsize=(20,8))
ax = sns.distplot(df['life_expectancy'])
plt.title('Count of life expectancy')
plt.xticks(rotation=45)
plt.ylabel('count')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to u
se either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[22]:

```
Text(0, 0.5, 'count')
```



In [23]:

```
columns_dict={'life_expectancy': 1, 'adult_mortality': 2, 'infant_deaths': 3, 'alcohol': 4,
              'percentage_expenditure': 5, 'hepatitis_b': 6, 'measles': 7, 'bmi': 8, 'under-five_deaths': 9,
              'polio': 10, 'total_expenditure': 11, 'diphtheria': 12, 'hiv/aids': 13, 'gdp': 14, 'population': 15,
              'thinness__1-19_years': 16, 'thinness_5-9_years': 17, 'income_composition_of_resources': 18,
              'schooling': 19}

plt.figure(figsize=(20,30) )

# make a histogram plot for each variable column
for variable,i in columns_dict.items():

  plt.subplot(5,4,i)
```

```
  sns.distplot(df[variable])
  sns.set(style='darkgrid')
  plt.title(variable)

plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to u
se either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
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  warnings.warn(msg, FutureWarning)
```
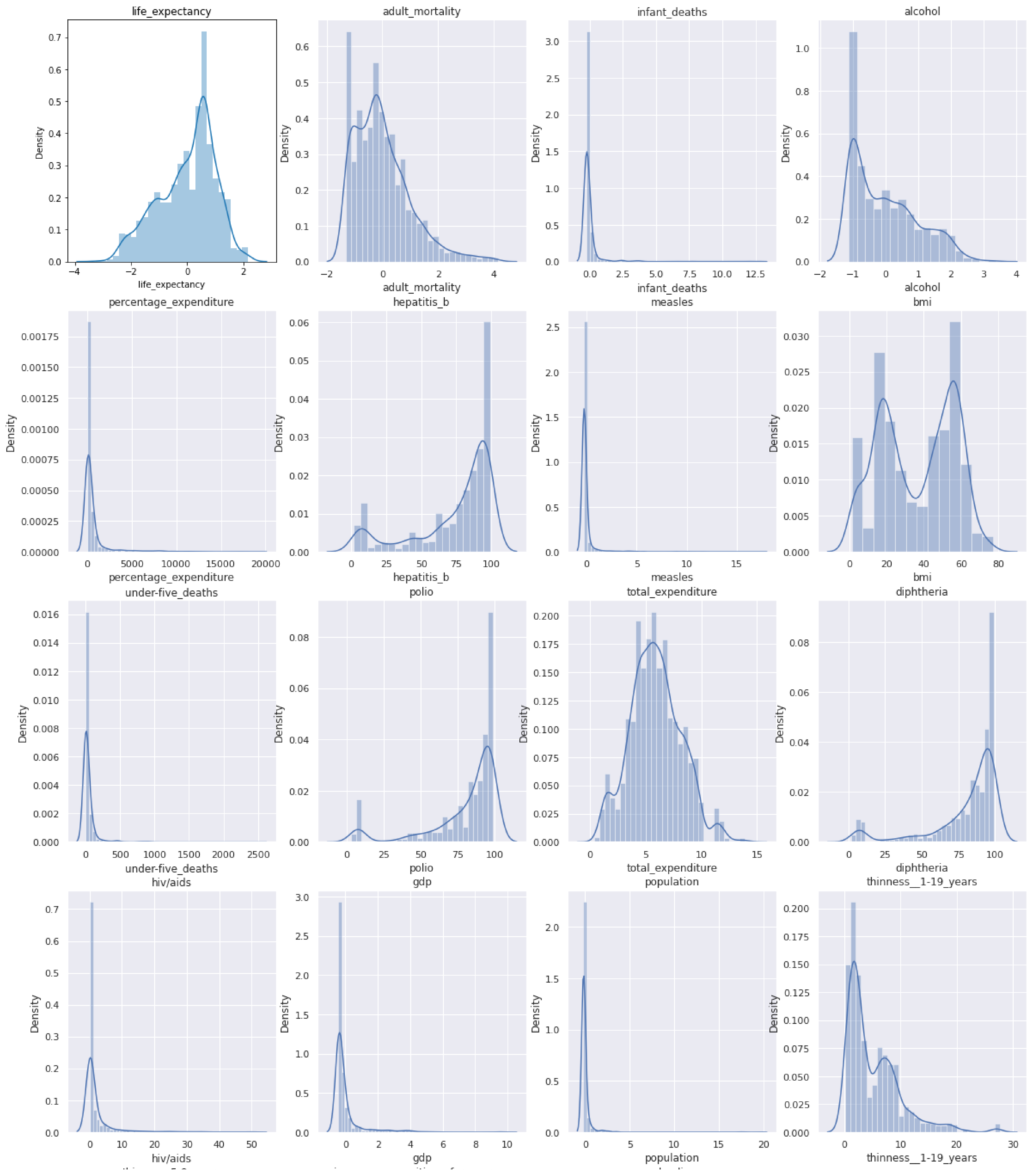
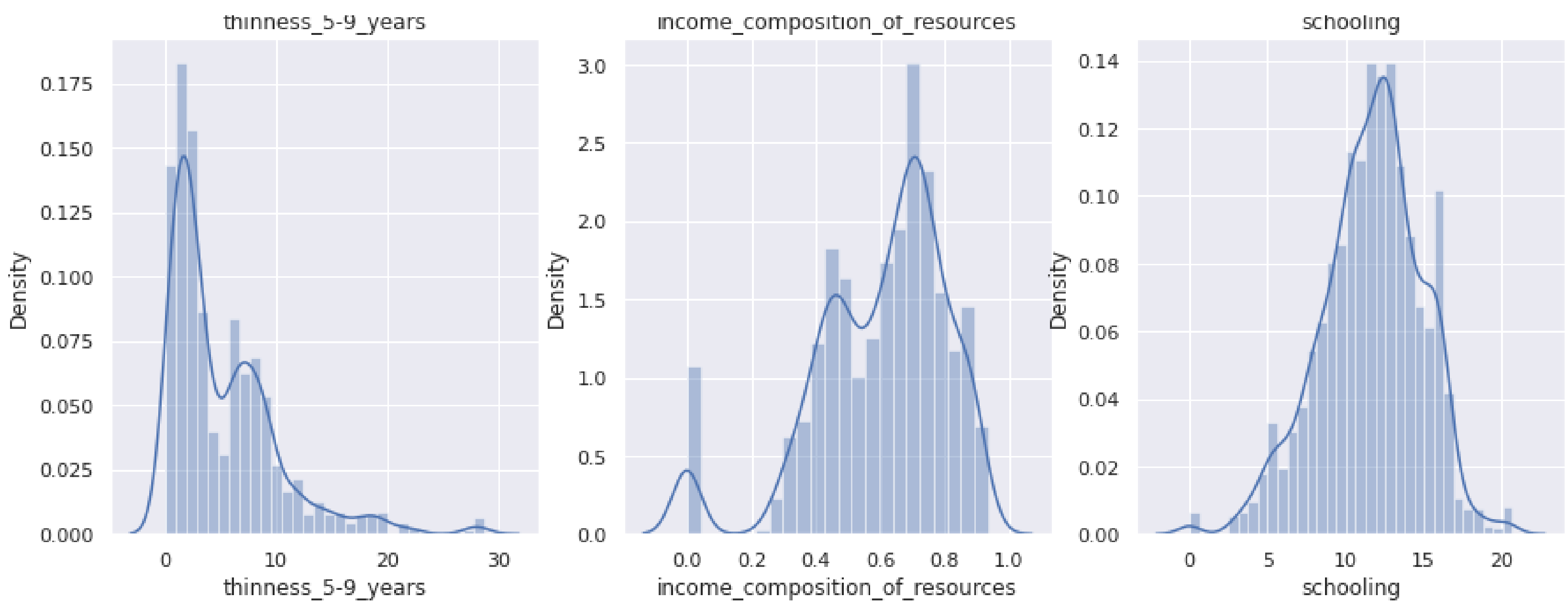





In [24]:

```
df_skew = df.drop('year', axis = 1)

print(df_skew.skew())
```

```
life_expectancy                   -0.531505
adult_mortality                    1.140995
infant_deaths                      8.568802
alcohol                            0.695528
percentage_expenditure             4.762827
hepatitis_b                       -1.311729
measles                            8.764714
bmi                               -0.095303
under-five_deaths                  8.316159
polio                             -1.881600
total_expenditure                  0.238713
diphtheria                        -1.903185
hiv/aids                           4.544181
gdp                                4.298171
population                        15.140323
thinness__1-19_years               1.657464
thinness_5-9_years                 1.715890
income_composition_of_resources   -1.014837
schooling                         -0.373064
dtype: float64
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future ver
sion this will raise TypeError.  Select only valid columns before calling the reduction.
  This is separate from the ipykernel package so we can avoid doing imports until
```

Findings

- **There are more developing countries than developed countries**
- **Most of the data appears to be normally distributed**
- **The columns life expectancy, hepatitis b, bmi, polio, diphteria, income composition of resources and schooling are negatively skewed to the left while the rest are positively skewed to the right**

Calculating P value

Bivariate Analysis

In [25]:

```
df.columns
```

Out[25]:

```
Index(['country', 'year', 'status', 'life_expectancy', 'adult_mortality',
       'infant_deaths', 'alcohol', 'percentage_expenditure', 'hepatitis_b',
       'measles', 'bmi', 'under-five_deaths', 'polio', 'total_expenditure',
       'diphtheria', 'hiv/aids', 'gdp', 'population', 'thinness__1-19_years',
       'thinness_5-9_years', 'income_composition_of_resources', 'schooling'],
      dtype='object')
```

In [26]:

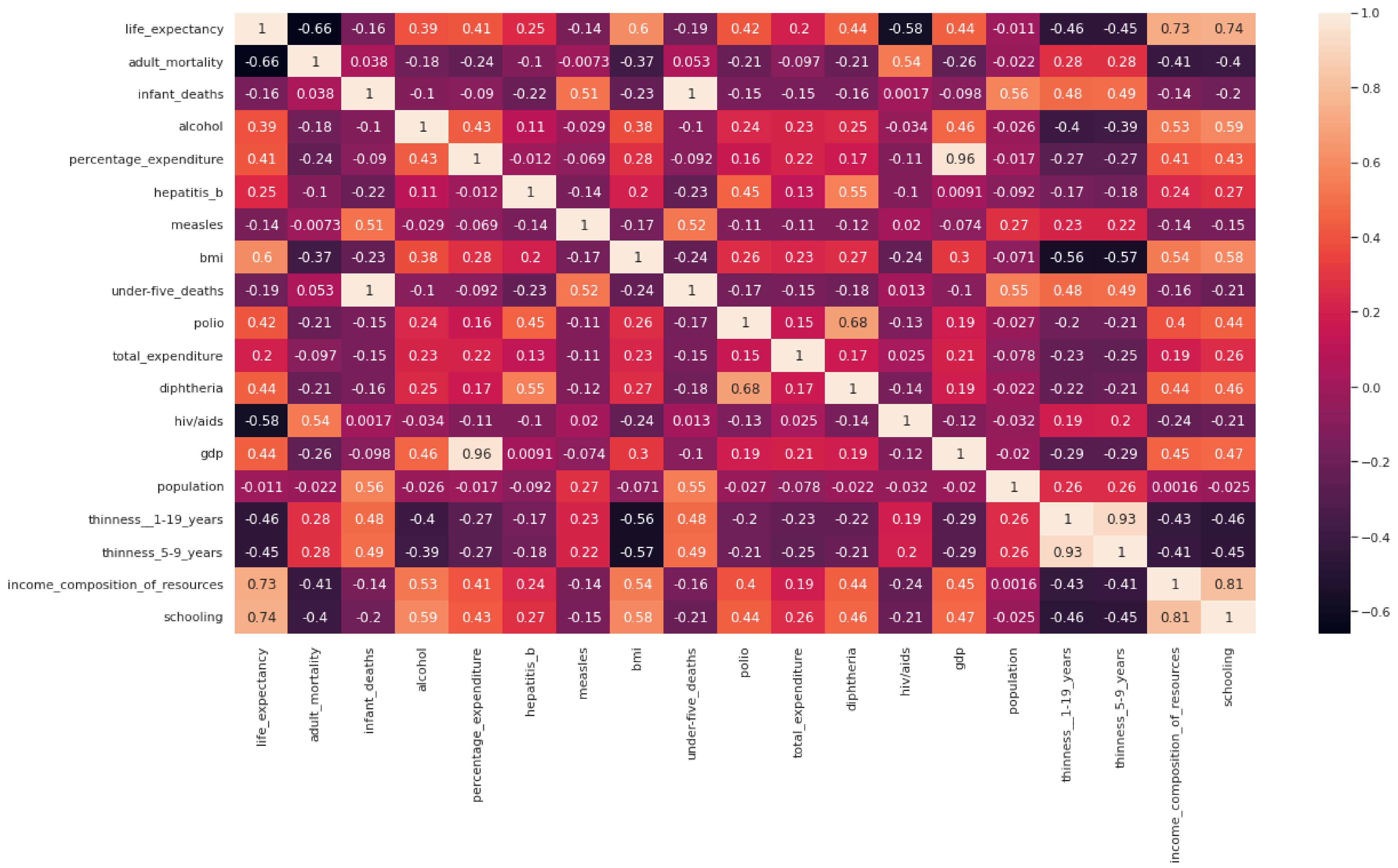
```
# pick out the columns needed to plot
needed= df.drop(['country','year'], axis=1)
```

In [27]:

```
#Heatmap
plt.figure(figsize=(20,10))
sns.heatmap(needed.corr(), annot=True)
```

Out[27]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fea5cd0e550>
```



- **Life expectancy:**
  - There is a **negative correlation** between life expectancy and the following fields: adult mortality, hiv/aids and thinness of both 1-19 years and 5-9 years.
    - This suggests that if more adults die, more infants die from hiv/aids and if more of the population is thin(from poor nutrition) life expectancy is expected to go lower
  - There is a **positive correlation** between life expectancy and the following fields: bmi, schooling and income composition of resources

- There is a **positive correlation** between life expectancy and the following fields: bmi, schooling and income composition of resources
- There is a **positive correlation** between adult mortality rate and hiv/aids suggesting that most adult deaths occur from hiv/aids compared to infant deaths
- There is a **positive** correlation between infant deaths and measles, population and thinness. This suggests that most infant deaths that occur are due to measles and poor nutrition
- There is a positively high correlation between alcohol and income composition of resources and schooling. This suggests that more people who have a higher income and have schooled for more years are more prone to consuming alcohol.
- There is a very high positive correlation of 0.96 between percentage expenditure on health and gdp of a country. If a countries gdp is high, it is expected that a larger percentage is directed towards the health sector.
- Hepatitis b is positively correlated with polio and diphteria. They are all immunizable diseases.
- BMI is positively correlated with schooling and income composition of resources and negatively correlated with thinness. Going to school ensures that a population is fed and hence improved nutrition.

C. Building a Pipeline

In [28]:

```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import linear_model
```

In [29]:

```
class Removing_Outliers:
    def fit(self):pass
    def transform(self, train1):
        train1 = train1[train1['life_expectancy']>0]
        train1 = train1[train1['adult_mortality']>0]
        train1 = train1[train1['alcohol']>0]
        train1 = train1[train1['hepatitis_b']>0]
        train1 = train1[train1['bmi']>0]
        train1 = train1[train1['total_expenditure']>0]
        train1 = train1[train1['gdp']>0]
        # train1 = train1[train1['population']>0]
        train1 = train1[train1['thinness__1-19_years']>0]
        train1 = train1[train1['thinness_5-9_years']>0]
        train1 = train1[train1['income_composition_of_resources']>0]
        train1 = train1[train1['schooling']>0]
        return train1



class Features_Selection:
    def fit(self):pass
    def transform(self, train1):
        train1['key'] = pd.to_datetime(train1['key'])
        train1['pickup_datetime']  = pd.to_datetime(train1['pickup_datetime'])
        train1['year'] = train1['pickup_datetime'].dt.year
        train1['Month'] = train1['pickup_datetime'].dt.month
        train1['Date'] = train1['pickup_datetime'].dt.day
        train1['Day of Week'] = train1['pickup_datetime'].dt.dayofweek
        train1['Hour'] = train1['pickup_datetime'].dt.hour
        train1 = train1.reset_index()

        return train1

class Transform:
    def fit(self):pass
    def transform(self, train1):
        scalar = StandardScaler()
        scaled_train_data = train1
        scaled_train_data["life_expectancy"]=scalar.fit_transform(train1[["life_expectancy"]])
        scaled_train_data["adult_mortality"]=scalar.fit_transform(train1[["adult_mortality"]])
        scaled_train_data["infant_deaths"]=scalar.fit_transform(train1[["infant_deaths"]])
        scaled_train_data["alcohol"]=scalar.fit_transform(train1[["alcohol"]])
        scaled_train_data['measles']=scalar.fit_transform(train1[['measles']])
        scaled_train_data["gdp"]=scalar.fit_transform(train1[["gdp"]])
        # scaled_train_data["population"]=scalar.fit_transform(train1[["population"]])
        return scaled_train_data


pipe = Pipeline([
    ('anomaly remover', Removing_Outliers()),

    # ('features selection', Features_Selection()),
    ('scaler', Transform())
])
```

In [30]:

```
data = train2
data = pipe.transform(data)
print(' Resulting dataframe:', data.shape)
data.sample(n=10)
```

```
 Resulting dataframe: (40, 22)
```

Out[30]:

	country	year	status	life_expectancy	adult_mortality	infant_deaths	alcohol	percentage_expenditure	hepatitis_b	measles	bmi	under-five_deaths	polio	total_expenditure	diphtheria	hiv/aids	gdp	population	thinness__1-19_years	thinness_5-9_years	income_comp
2480	Suriname	2008	Developing	-0.913511	-0.268108	-0.400507	-1.356448	815.435599	84.0	-0.297692	53.3	0	85.0	5.92	85.0	1.2	-1.207108	-0.201415	3.5	3.4	
2663	Trinidad and Tobago	2001	Developing	-1.244407	-0.326551	-0.400507	-1.462761	516.711248	5.0	-0.297692	34.4	1	91.0	4.40	91.0	1.2	-1.185373	-0.207393	6.6	7.1	
2137	Russian Federation	2013	Developing	-0.818969	0.696205	1.365509	0.181005	1529.497771	97.0	2.405339	59.3	16	98.0	7.90	97.0	0.2	1.226885	0.011914	2.3	2.3	
1350	Kazakhstan	2011	Developing	-1.528033	0.550097	0.482501	-0.895757	179.170133	99.0	-0.150926	49.9	7	99.0	4.60	99.0	0.1	0.131372	-0.206802	2.3	2.5	
1532	Lithuania	2005	Developed	2.962705	0.491653	-0.400507	0.649874	913.699529	95.0	-0.296536	58.4	0	93.0	5.83	94.0	0.1	-0.925471	-0.158148	3.0	3.1	
2475	Suriname	2013	Developing	-0.251718	-0.764875	-0.400507	-1.062042	1122.972967	86.0	-0.297692	57.0	0	86.0	5.96	86.0	0.4	-0.471094	-0.208518	3.5	3.5	
2477	Suriname	2011	Developing	2.017287	-0.531103	-0.400507	-1.165629	989.126356	86.0	-0.297692	55.5	0	86.0	5.93	86.0	0.1	-0.797735	-0.201161	3.5	3.4	
1451	Latvia	2006	Developed	1.544577	0.696205	-0.400507	0.131937	1099.248837	94.0	-0.289602	57.4	0	96.0	6.80	96.0	0.1	-0.419697	-0.175165	2.4	2.5	
875	Estonia	2006	Developing	0.599159	-0.501881	-0.400507	1.816593	244.351080	95.0	-0.266489	55.9	0	95.0	5.10	95.0	0.1	0.400677	-0.207278	2.1	2.2	
2656	Trinidad and Tobago	2008	Developing	-0.866240	-0.589546	-0.400507	-0.955729	1902.693048	9.0	-0.297692	4.2	0	91.0	4.40	9.0	0.3	2.808660	-0.189082	6.1	6.4	

In [30]:

Use of Validation Set and Cross Validation Approach

In [31]:

```
from sklearn import datasets
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import KFold, cross_val_score

X, y = datasets.load_iris(return_X_y=True)

clf = DecisionTreeClassifier(random_state=42)

k_folds = KFold(n_splits = 10)

scores = cross_val_score(clf, X, y, cv = k_folds)

print("Cross Validation Scores: ", scores)
```

```
print("Average CV Score: ", scores.mean())
print("Number of CV Scores used in Average: ", len(scores))
```

```
Cross Validation Scores:  [1.         1.         1.         0.93333333 0.93333333 0.86666667
 1.         0.86666667 0.93333333 1.        ]
Average CV Score:  0.9533333333333334
Number of CV Scores used in Average:  10
```

In [31]:

```

```

Ordinary least squares Method (OLS)

Spplitting Data Set

In [32]:

```
# import all libraries and dependencies for machine learning
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
import statsmodels.api as sm
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.metrics import mean_absolute_error, mean_squared_error,r2_score
```

In [33]:

```
X=df.drop(columns=['life_expectancy','country'])

y=df[['life_expectancy']]

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_state=1234)
```

In [34]:

```
from sklearn import datasets
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import KFold, cross_val_score

X, y = datasets.load_iris(return_X_y=True)

clf = DecisionTreeClassifier(random_state=42)

k_folds = KFold(n_splits = 10)

scores = cross_val_score(clf, X, y, cv = k_folds)

print("Cross Validation Scores: ", scores)
print("Average CV Score: ", scores.mean())
print("Number of CV Scores used in Average: ", len(scores))
```


```
Cross Validation Scores:  [1.         1.         1.         0.93333333 0.93333333 0.86666667
 1.         0.86666667 0.93333333 1.        ]
Average CV Score:  0.9533333333333334
Number of CV Scores used in Average:  10
```


In [34]:

```

```

Models

Building model with 1 variable

In [35]:

```
X_train1 = X_train['income_composition_of_resources']
```

In [36]:

```
# Add a constant
X_train1 = sm.add_constant(X_train1)

# Create a first ols model
model_1 = sm.OLS(y_train, X_train1).fit()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pandas all arguments of concat except for the argument 'objs' will be keyword-o
nly
  x = pd.concat(x[::order], 1)
```

In [37]:

```
# Check parameters created
model_1.params
```

Out[37]:

```
const                             -2.316241
income_composition_of_resources    3.802101
dtype: float64
```

In [38]:

```
print(model_1.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:        life_expectancy   R-squared:                       0.572
Model:                            OLS   Adj. R-squared:                  0.572
Method:                 Least Squares   F-statistic:                     1855.
Date:                Sun, 21 Aug 2022   Prob (F-statistic):          4.31e-258
Time:                        02:24:10   Log-Likelihood:                -1399.6
No. Observations:                1390   AIC:                             2803.
Df Residuals:                    1388   BIC:                             2814.
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
===================================================================================================
                                      coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------
const                              -2.3162      0.056    -41.031      0.000      -2.427      -2.206
income_composition_of_resources     3.8021      0.088     43.074      0.000       3.629       3.975
==============================================================================
Omnibus:                      151.290   Durbin-Watson:                   1.984
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              681.058
Skew:                           0.418   Prob(JB):                    1.29e-148
Kurtosis:                       6.326   Cond. No.                         6.85
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Building model with 2 variable

In [39]:

```
X_train2 = X_train[['income_composition_of_resources','schooling']]
```

In [40]:

```
# Add a constant
X_train2 = sm.add_constant(X_train2)

# Create second ols model
model_2 = sm.OLS(y_train, X_train2).fit()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pandas all arguments of concat except for the argument 'objs' will be keyword-o
nly
  x = pd.concat(x[::order], 1)
```

In [41]:

```python
# Check parameters created
model_2.params
```

Out[41]:

```
const                           -2.779635
income_composition_of_resources    2.138827
schooling                          0.126380
dtype: float64
```

In [42]:

```python
# Summary of the model
print(model_2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        life_expectancy   R-squared:                       0.624
Model:                            OLS   Adj. R-squared:                  0.624
Method:                 Least Squares   F-statistic:                     1152.
Date:                Sun, 21 Aug 2022   Prob (F-statistic):          1.49e-295
Time:                        02:24:10   Log-Likelihood:                -1309.2
No. Observations:                1390   AIC:                             2624.
Df Residuals:                    1387   BIC:                             2640.
Df Model:                           2
Covariance Type:            nonrobust
===================================================================================================
                                      coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------
const                              -2.7796      0.063    -44.431      0.000      -2.902      -2.657
income_composition_of_resources     2.1388      0.146     14.691      0.000       1.853       2.424
schooling                           0.1264      0.009     13.884      0.000       0.109       0.144
==============================================================================
Omnibus:                       92.129   Durbin-Watson:                   1.978
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              340.263
Skew:                          -0.210   Prob(JB):                     1.30e-74
Kurtosis:                       5.387   Cond. No.                         106.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

Building model with 3 variable

In [43]:

```python
# Adding one more feature in regression model
X_train3 = X_train[['income_composition_of_resources','schooling', 'adult_mortality']]
```

In [44]:

```python
# Add a constant
X_train3 = sm.add_constant(X_train3)

# Create third fitted model
model_3 = sm.OLS(y_train, X_train3).fit()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.py:142: FutureWarning: In a future version of pandas all arguments of concat except for the argument 'objs' will be keyword-o
nly
  x = pd.concat(x[::order], 1)
```

In [45]:

```python
# Check parameters created
model_3.params
```

Out[45]:

```
const                           -2.213270
income_composition_of_resources    1.596823
schooling                          0.106026
adult_mortality                   -0.383420
dtype: float64
```

In [46]:

```python
# Summary of the model
print(model_3.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        life_expectancy   R-squared:                       0.741
Model:                            OLS   Adj. R-squared:                  0.740
Method:                 Least Squares   F-statistic:                     1321.
Date:                Sun, 21 Aug 2022   Prob (F-statistic):               0.00
Time:                        02:24:10   Log-Likelihood:                -1051.0
No. Observations:                1390   AIC:                             2110.
Df Residuals:                    1386   BIC:                             2131.
Df Model:                           3
Covariance Type:            nonrobust
===================================================================================================
                                      coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------
const                              -2.2133      0.057    -39.028      0.000      -2.325      -2.102
income_composition_of_resources     1.5968      0.123     12.994      0.000       1.356       1.838
schooling                           0.1060      0.008     13.939      0.000       0.091       0.121
adult_mortality                    -0.3834      0.015    -24.968      0.000      -0.414      -0.353
==============================================================================
Omnibus:                      168.279   Durbin-Watson:                   1.998
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              817.571
Skew:                          -0.460   Prob(JB):                    2.93e-178
Kurtosis:                       6.643   Cond. No.                         108.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

In [46]:

Kolmogorov–Smirnov test

In [47]:

```python
import scipy.stats as stats
stats.ttest_ind(df.loc[df['status']=='Developed','life_expectancy'],df.loc[df['status']=='Developing','life_expectancy'])
```

Out[47]:

```
Ttest_indResult(statistic=22.924393771134888, pvalue=2.2504696584331004e-103)
```

Testing

In [47]:

Distribution analysis

We wish to investigate whether there is a statistically significant difference in the mean life expectancy between developing and developed countries at a significance level of 5%

Is this value greater in developed countries than in developing countries?

- **Null Hypothesis, H0: the mean life expectancy equal/similar in developed and developing countries from 2000-2015**
- **Alternate Hypothesis, H1: the mean life expectancy is not equal in developed and developing countries(is it lower or higher)(claim)**

In [48]:

```
# select the specific columns to investigate
df1=df[['country', 'life_expectancy', 'status', 'year', 'polio']]
df1.head()
```

Out[48]:

	country	life_expectancy	status	year	polio
0	Afghanistan	-0.307275	Developing	2015	6.0
1	Afghanistan	-0.832833	Developing	2014	58.0
2	Afghanistan	-0.832833	Developing	2013	62.0
3	Afghanistan	-0.874054	Developing	2012	67.0
4	Afghanistan	-0.904969	Developing	2011	68.0

In [49]:

```
#Encoding the status column
df1['status'] = df1.status.map({'Developing': 0, 'Developed': 1})
print(df1.head())
#Changing the data type of status column to integer
df1['status']= df1['status'].astype(int)
#Grouping by country and status
df3=df1.groupby(['country', 'status'])['life_expectancy'].mean()
df3
```

```
       country  life_expectancy  status  year  polio
0  Afghanistan        -0.307275       0  2015    6.0
1  Afghanistan        -0.832833       0  2014   58.0
2  Afghanistan        -0.832833       0  2013   62.0
3  Afghanistan        -0.874054       0  2012   67.0
4  Afghanistan        -0.904969       0  2011   68.0
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """
```

Out[49]:

```
country      status
Afghanistan  0        -1.008664
Albania      0         0.739334
Algeria      0         0.567282
Angola       0        -1.977384
Argentina    0         0.731477
                         ...
Uruguay      0         0.827657
Uzbekistan   0        -0.004306
Vanuatu      0         0.346754
Zambia       0        -1.504724
Zimbabwe     0        -1.916240
Name: life_expectancy, Length: 133, dtype: float64
```

In [50]:

```
# save the grouped data as a csv file
df3.to_csv("hypothesis.csv")
df3 = pd.read_csv("hypothesis.csv")
df3.head()
```

Out[50]:

	country	status	life_expectancy
0	Afghanistan	0	-1.008664
1	Albania	0	0.739334
2	Algeria	0	0.567282
3	Angola	0	-1.977384
4	Argentina	0	0.731477

In [51]:

```
df3['status'].value_counts()

# there is a total of 114 developing countries and 19 developed countries in the data
```

Out[51]:

```
0    114
1     19
Name: status, dtype: int64
```

In [52]:

```
# select only developing countries onto a new dataframe
developing = df3.loc[df3.status == 0]
developing.head()
```

Out[52]:

	country	status	life_expectancy
0	Afghanistan	0	-1.008664
1	Albania	0	0.739334
2	Algeria	0	0.567282
3	Angola	0	-1.977384
4	Argentina	0	0.731477

In [53]:

```
# select only developed countries
developed = df3.loc[df3.status == 1]
developed.head()
```

Out[53]:

	country	status	life_expectancy
6	Australia	1	1.418481
7	Austria	1	1.391001
11	Belgium	1	1.305813
18	Bulgaria	1	0.490338
32	Croatia	1	0.825596

Sampling

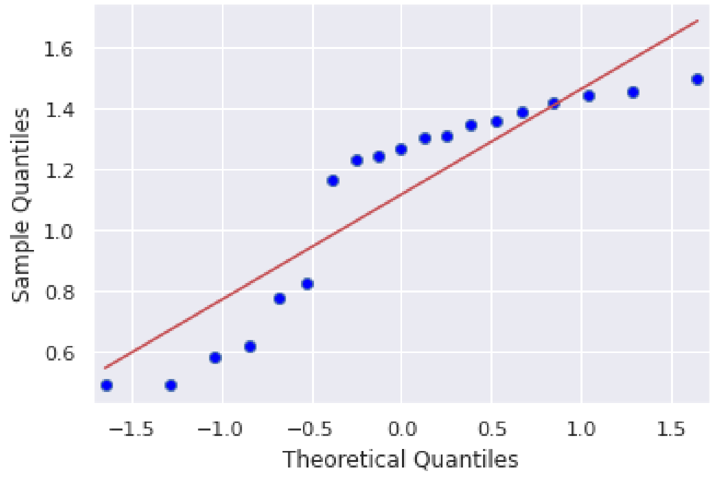
Sampling in this project did not seem to be the best option to undertake as there are few countries in our population. Sampling would reduce the size of data size to investigate and leading to inappropriate conclusions, hence we decided

Sampling in this project did not seem to be the best option to undertake as there are few countries in our population. Sampling would reduce the size of data size to investigate and leading to inappropriate conclusions, hence we decided to work with the whole population.

Normality Testing

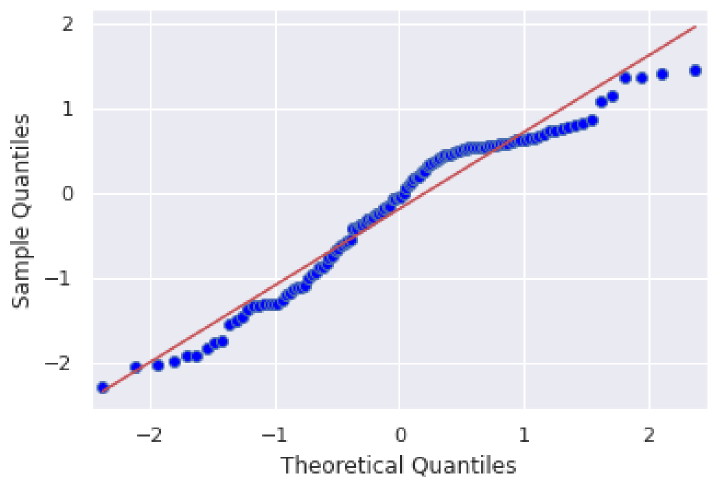
In [54]:

```
#Checking if the data in the developed countries is normally distributed
from statsmodels.graphics.gofplots import qqplot
from matplotlib import pyplot

# q-q plot
qqplot(developed['life_expectancy'], line='s')
plt.show()

#It is normally distributed therefore we can perform the statistic tests.
```



In [55]:

```
# normality test for the life expectancy in developing countries
qqplot(developing['life_expectancy'], line='s')
plt.show()
```



From both populations, the data is normally distributed about the mean

Statistical Testing

https://www.analyticsvidhya.com/blog/2021/06/feature-selection-using-statistical-tests/

This is a two-tailed test, using a Z statistic(since sample size > 30) and a 5% level of significance.

The critical region defined for a two-tailed z-test at 0.05 significance level is 1.960.

Therefore, Reject the null hypothesis if Z < -1.960 or is Z > 1.960.

In [56]:

```
# compute the means for both populations
mean_developing = developing['life_expectancy'].mean()
mean_developed = developed['life_expectancy'].mean()

print(f"The mean life expectancy of developing countries: {mean_developing}")
print(f"The mean life expectancy of developed countries: {mean_developed}")
# compute the standard deviations for both populations
s1 = developing['life_expectancy'].std()
s2 = developed['life_expectancy'].std()

# compute the count/number in each population
n1 = developing['life_expectancy'].count()
n2 = developed['life_expectancy'].count()
print(f"S1 is: {s1} while s2 is: {s2}")
print("..............")
import math

# pooled estimate of the common stadard deviation
sp = math.sqrt(((n1-1)*s1**2+(n2-1)*s2**2)/(n1+n2-2))

print(f"The pooled estimate of the commom stdev is: {round(sp,3)}, which is a value between {round(s1,3)} and {round(s2,3)}")
# sp is a number between the standard deviations of both stdev of both samples
```

```
The mean life expectancy of developing countries: -0.18553252915903234
The mean life expectancy of developed countries: 1.1180795072759842
S1 is: 0.9071404526470805 while s2 is: 0.3569085389198975
..............
The pooled estimate of the commom stdev is: 0.853, which is a value between 0.907 and 0.357
```

In [57]:

```
# z-score
```

Out[57]:

```
-6.1685654840735795
```

The z-score is less than -1.960. It falls within the critical region defined by Z < -1.960 or is Z > 1.960.

Therefore, we reject the null hypothesis and accept the alternate hypothesis that the mean life expectancy between the developed and developing countries is different

There is enough statistical significance evidence at α=0.05 to show that there is a difference between the mean life expectancy of developed and ddeveloping countries

In [58]:

```
#Performing the test statistic using python's scipy stats library:

# importing libraries
from scipy import stats
from statsmodels.stats import weightstats as stests

# computing the z_test and p-value
ztest ,pval1 = stests.ztest(developing['life_expectancy'], developed['life_expectancy'], value=0,alternative='two-sided')
print(ztest, pval1)
if pval1 < 0.05:
    print("reject null hypothesis and accept the alternate hypothesis")
else:
    print("accept null hypothesis")
```

```
-6.1685654840735795 6.891231036467287e-10
reject null hypothesis and accept the alternate hypothesis
```

In [59]:

```
# difference of the two means
diff = mean_developed-mean_developing
diff
```

Out[59]:

```
1.3036120364350166
```

The p-value is less than the set alpha level of 0.05. We reject the null hypothesis and accept the alternate hypothesis

Here again, we find that there is enough statistical evidence to show that there is a difference between mean of the life expectancy of developed and developing countries.

Notice that there is a difference in the two means is 1.3 which indicates a significant difference

Conclusion: Life expectancy in developed countries is higher than in developing countries