Final Project

December 13, 2022

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.express as px
import seaborn as sns
import datetime as dt
import warnings
```

Data upload

[78]:
```
df = pd.read_csv('/Users/polina/Desktop/Life Expectancy Data.csv')
df
```

[78]:

	Country	Year	Status	Life expectancy	Adult Mortality	infant deaths	Alcohol	percentage expenditure	Hepatitis B	Measles
0	Afghanistan	2015	Developing	65.0	263.0	62	0.01	71.279624	65.0	1154
1	Afghanistan	2014	Developing	59.9	271.0	64	0.01	73.523582	62.0	492
2	Afghanistan	2013	Developing	59.9	268.0	66	0.01	73.219243	64.0	430
3	Afghanistan	2012	Developing	59.5	272.0	69	0.01	78.184215	67.0	2787
4	Afghanistan	2011	Developing	59.2	275.0	71	0.01	7.097109	68.0	3013
…	…	…	…	…	…	…	…	…	…	…
2933	Zimbabwe	2004	Developing	44.3	723.0	27	4.36	0.000000	68.0	31
2934	Zimbabwe	2003	Developing	44.5	715.0	26	4.06	0.000000	7.0	998
2935	Zimbabwe	2002	Developing	44.8	73.0	25	4.43	0.000000	73.0	304
2936	Zimbabwe	2001	Developing	45.3	686.0	25	1.72	0.000000	76.0	529
2937	Zimbabwe	2000	Developing	46.0	665.0					

```
2937             24     1.68                0.000000         79.0      1483

      …  Polio  Total expenditure  Diphtheria    HIV/AIDS         GDP  \
0     …    6.0               8.16         65.0        0.1  584.259210
1     …   58.0               8.18         62.0        0.1  612.696514
2     …   62.0               8.13         64.0        0.1  631.744976
3     …   67.0               8.52         67.0        0.1  669.959000
4     …   68.0               7.87         68.0        0.1   63.537231
…   …    …                 …           …         …          …
2933  …   67.0               7.13         65.0       33.6  454.366654
2934  …    7.0               6.52         68.0       36.7  453.351155
2935  …   73.0               6.53         71.0       39.8   57.348340
2936  …   76.0               6.16         75.0       42.1  548.587312
2937  …   78.0               7.10         78.0       43.5  547.358878

      Population   thinness  1-19 years   thinness 5-9 years  \
0     33736494.0                   17.2                 17.3
1       327582.0                   17.5                 17.5
2     31731688.0                   17.7                 17.7
3      3696958.0                   17.9                 18.0
4      2978599.0                   18.2                 18.2
…          …                      …                    …
2933  12777511.0                    9.4                  9.4
2934  12633897.0                    9.8                  9.9
2935    125525.0                    1.2                  1.3
2936  12366165.0                    1.6                  1.7
2937  12222251.0                   11.0                 11.2

      Income composition of resources  Schooling
0                               0.479       10.1
1                               0.476       10.0
2                               0.470        9.9
3                               0.463        9.8
4                               0.454        9.5
…                               …          …
2933                            0.407        9.2
2934                            0.418        9.5
2935                            0.427       10.0
2936                            0.427        9.8
2937                            0.434        9.8

[2938 rows x 22 columns]
```

Data Info

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

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 2938 entries, 0 to 2937
Data columns (total 22 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   Country                          2938 non-null   object
 1   Year                             2938 non-null   int64
 2   Status                           2938 non-null   object
 3   Life expectancy                  2928 non-null   float64
 4   Adult Mortality                  2928 non-null   float64
 5   infant deaths                    2938 non-null   int64
 6   Alcohol                          2744 non-null   float64
 7   percentage expenditure           2938 non-null   float64
 8   Hepatitis B                      2385 non-null   float64
 9   Measles                          2938 non-null   int64
 10   BMI                             2904 non-null   float64
 11  under-five deaths                2938 non-null   int64
 12  Polio                            2919 non-null   float64
 13  Total expenditure                2712 non-null   float64
 14  Diphtheria                       2919 non-null   float64
 15   HIV/AIDS                        2938 non-null   float64
 16  GDP                              2490 non-null   float64
 17  Population                       2286 non-null   float64
 18   thinness  1-19 years            2904 non-null   float64
 19   thinness 5-9 years             2904 non-null   float64
 20  Income composition of resources  2771 non-null   float64
 21  Schooling                        2775 non-null   float64
dtypes: float64(16), int64(4), object(2)
memory usage: 505.1+ KB
```

[80]:
```
df.shape
```

[80]:
```
(2938, 22)
```

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

[81]:
```
              Year  Life expectancy   Adult Mortality  infant deaths  \
count  2938.000000       2928.000000      2928.000000    2938.000000
mean   2007.518720         69.224932       164.796448      30.303948
std       4.613841          9.523867       124.292079     117.926501
min    2000.000000         36.300000         1.000000       0.000000
25%    2004.000000         63.100000        74.000000       0.000000
50%    2008.000000         72.100000       144.000000       3.000000
75%    2012.000000         75.700000       228.000000      22.000000
max    2015.000000         89.000000       723.000000    1800.000000

           Alcohol  percentage expenditure  Hepatitis B       Measles   \
count  2744.000000             2938.000000  2385.000000    2938.000000
mean      4.602861              738.251295    80.940461    2419.592240
```

std	4.052413	1987.914858	25.070016	11467.272489
min	0.010000	0.000000	1.000000	0.000000
25%	0.877500	4.685343	77.000000	0.000000
50%	3.755000	64.912906	92.000000	17.000000
75%	7.702500	441.534144	97.000000	360.250000
max	17.870000	19479.911610	99.000000	212183.000000

	BMI	under-five deaths	Polio	Total expenditure	\
count	2904.000000	2938.000000	2919.000000	2712.00000	
mean	38.321247	42.035739	82.550188	5.93819	
std	20.044034	160.445548	23.428046	2.49832	
min	1.000000	0.000000	3.000000	0.37000	
25%	19.300000	0.000000	78.000000	4.26000	
50%	43.500000	4.000000	93.000000	5.75500	
75%	56.200000	28.000000	97.000000	7.49250	
max	87.300000	2500.000000	99.000000	17.60000	

	Diphtheria	HIV/AIDS	GDP	Population	\
count	2919.000000	2938.000000	2490.000000	2.286000e+03	
mean	82.324084	1.742103	7483.158469	1.275338e+07	
std	23.716912	5.077785	14270.169342	6.101210e+07	
min	2.000000	0.100000	1.681350	3.400000e+01	
25%	78.000000	0.100000	463.935626	1.957932e+05	
50%	93.000000	0.100000	1766.947595	1.386542e+06	
75%	97.000000	0.800000	5910.806335	7.420359e+06	
max	99.000000	50.600000	119172.741800	1.293859e+09	

	thinness 1-19 years	thinness 5-9 years	\
count	2904.000000	2904.000000	
mean	4.839704	4.870317	
std	4.420195	4.508882	
min	0.100000	0.100000	
25%	1.600000	1.500000	
50%	3.300000	3.300000	
75%	7.200000	7.200000	
max	27.700000	28.600000	

	Income composition of resources	Schooling
count	2771.000000	2775.000000
mean	0.627551	11.992793
std	0.210904	3.358920
min	0.000000	0.000000
25%	0.493000	10.100000
50%	0.677000	12.300000
75%	0.779000	14.300000
max	0.948000	20.700000

Data Cleaning

[82]:
```
# Looking for null value in the data
df.isnull().sum()
```

[82]:
```
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
```

[83]:
```
# Replacing the Null Values with mean values of the data
from sklearn.impute import SimpleImputer
#reference: https://scikit-learn.org/stable/modules/generated/sklearn.impute.
 ↪SimpleImputer.html
imputer=SimpleImputer(missing_values=np.nan,strategy='mean',fill_value=None)
df['Life expectancy ']=imputer.fit_transform(df[['Life expectancy ']])
df['Adult Mortality']=imputer.fit_transform(df[['Adult Mortality']])
df['Alcohol']=imputer.fit_transform(df[['Alcohol']])
df['Hepatitis B']=imputer.fit_transform(df[['Hepatitis B']])
df[' BMI ']=imputer.fit_transform(df[[' BMI ']])
df['Polio']=imputer.fit_transform(df[['Polio']])
df['Total expenditure']=imputer.fit_transform(df[['Total expenditure']])
df['Diphtheria ']=imputer.fit_transform(df[['Diphtheria ']])
df['GDP']=imputer.fit_transform(df[['GDP']])
df['Population']=imputer.fit_transform(df[['Population']])
df[' thinness  1-19 years']=imputer.fit_transform(df[[' thinness  1-19 years']])
df[' thinness 5-9 years']=imputer.fit_transform(df[[' thinness 5-9 years']])
df['Income composition of resources']=imputer.fit_transform(df[['Income␣
 ↪composition of resources']])
df['Schooling']=imputer.fit_transform(df[['Schooling']])
```

[84]:
```
# Looking for null value in the data after fitting
df.isnull().sum()
```

[84]:
```
Country                            0
Year                               0
Status                             0
Life expectancy                    0
Adult Mortality                    0
infant deaths                      0
Alcohol                            0
percentage expenditure             0
Hepatitis B                        0
Measles                            0
 BMI                               0
under-five deaths                  0
Polio                              0
Total expenditure                  0
Diphtheria                         0
 HIV/AIDS                          0
GDP                                0
Population                         0
 thinness  1-19 years              0
 thinness 5-9 years                0
Income composition of resources    0
Schooling                          0
dtype: int64
```

[85]:
```
# Changing/Renaming the columns for easy access.
df = df.rename(columns={'Country': 'country', 'Year': 'year', 'Status':␣
 ↪'status', 'Life expectancy ': 'life_expectancy', 'Adult Mortality':␣
 ↪'adult_mortality',
       'infant deaths':'infant_death', 'Alcohol':'alcohol', 'percentage␣
 ↪expenditure': 'percentage_expenditure', 'Hepatitis B':'Hepatitis_b',
       'Measles ':'measles', ' BMI ':'bmi', 'under-five deaths ':
 ↪'under_five_deaths', 'Polio':'polio', 'Total expenditure':␣
 ↪'total_expenditure','Diphtheria ':'diphtheria', ' HIV/AIDS':'hiv_Aids',␣
 ↪'GDP':'gdp', 'Population':'population',
       ' thinness  1-19 years':'thinness_1_to_19', ' thinness 5-9 years':
 ↪'thinness_5_to_9',
       'Income composition of resources':'income_composition_of_resources',␣
 ↪'Schooling': 'schooling'})
```

[86]:
```
# Looking for columns after rename
df.columns
```

[86]:
```
Index(['country', 'year', 'status', 'life_expectancy', 'adult_mortality',
       'infant_death', 'alcohol', 'percentage_expenditure', 'Hepatitis_b',
```

```
       'measles', 'bmi', 'under_five_deaths', 'polio', 'total_expenditure',
       'diphtheria', 'hiv_Aids', 'gdp', 'population', 'thinness_1_to_19',
       'thinness_5_to_9', 'income_composition_of_resources', 'schooling'],
      dtype='object')
```

[87]:
```
#remove empty space
orig_cols = list(df.columns)
new_cols = []
for col in orig_cols:
    new_cols.append(col.strip().replace('  ', ' ').replace(' ', '_').lower())
df.columns = new_cols
```

[ ]:
```
# save the clean data into a CSV file
df.to_csv('clean_df.csv', index=False)
```

[ ]:
```
clean_df = pd.read_csv("clean_df.csv")
clean_df
```

Data Describe

[12]:
```
df.describe(include='object')
```

[12]:

	country	status
count	2938	2938
unique	193	2
top	Afghanistan	Developing
freq	16	2426

[13]:
```
#Top 10 Countries
print("Top 10 Countries with Most Life Expectancy")
print("="*50)
print(df.groupby("country").life_expectancy.mean().sort_values(ascending
 ↪=False).head(10))
print("="*50)
print("Top 10 Countries with Least Life Expectancy")
print("="*50)
print(df.groupby("country").life_expectancy.mean().sort_values(ascending =True).
 ↪head(10))
```

```
Top 10 Countries with Most Life Expectancy
==================================================
country
Japan          82.53750
Sweden         82.51875
Iceland        82.44375
Switzerland    82.33125
France         82.21875
Italy          82.18750
```

```
Spain          82.06875
Australia      81.81250
Norway         81.79375
Canada         81.68750
Name: life_expectancy, dtype: float64
================================================
Top 10 Countries with Least Life Expectancy
================================================
country
Sierra Leone                46.11250
Central African Republic    48.51250
Lesotho                     48.78125
Angola                      49.01875
Malawi                      49.89375
Chad                        50.38750
Côte d'Ivoire               50.38750
Zimbabwe                    50.48750
Swaziland                   51.32500
Nigeria                     51.35625
Name: life_expectancy, dtype: float64
```

[14]:
```
# Countries with Highest Life Expectancy
country_vs_life = df.groupby('country', as_index=False)['life_expectancy'].
  ↪mean()
country_vs_life.sort_values(by = 'life_expectancy', ascending=False).head(10)
```

[14]:

	country	life_expectancy
84	Japan	82.53750
165	Sweden	82.51875
75	Iceland	82.44375
166	Switzerland	82.33125
60	France	82.21875
82	Italy	82.18750
160	Spain	82.06875
7	Australia	81.81250
125	Norway	81.79375
30	Canada	81.68750

[15]:
```
# Countries with Lowest Life Expectancy
country_vs_life.sort_values(by = 'life_expectancy', ascending = True).head(10)
```

[15]:

	country	life_expectancy
152	Sierra Leone	46.11250
31	Central African Republic	48.51250
94	Lesotho	48.78125
3	Angola	49.01875
100	Malawi	49.89375
32	Chad	50.38750

```
44              Côte d'Ivoire         50.38750
192                  Zimbabwe         50.48750
164                 Swaziland         51.32500
123                   Nigeria         51.35625
```

[16]:
```
df.corr()['life_expectancy'].abs().sort_values(ascending=False)[1:]
```

[16]:
```
schooling                          0.715066
adult_mortality                    0.696359
income_composition_of_resources    0.692483
bmi                                0.559255
hiv_aids                           0.556457
diphtheria                         0.475418
thinness_1_to_19                   0.472162
thinness_5_to_9                    0.466629
polio                              0.461574
gdp                                0.430493
alcohol                            0.391598
percentage_expenditure             0.381791
under_five_deaths                  0.222503
total_expenditure                  0.207981
hepatitis_b                        0.203771
infant_death                       0.196535
year                               0.169623
measles                            0.157574
population                         0.019638
Name: life_expectancy, dtype: float64
```

[17]:
```
df["status"].value_counts()
```

[17]:
```
Developing    2426
Developed      512
Name: status, dtype: int64
```

[19]:
```
df.groupby(['status'])[["life_expectancy"]].mean()
```

[19]:
```
            life_expectancy
status
Developed         79.197852
Developing        67.120177
```

[20]:
```
corr = df.corr()
corr.style.background_gradient(cmap='coolwarm')
```

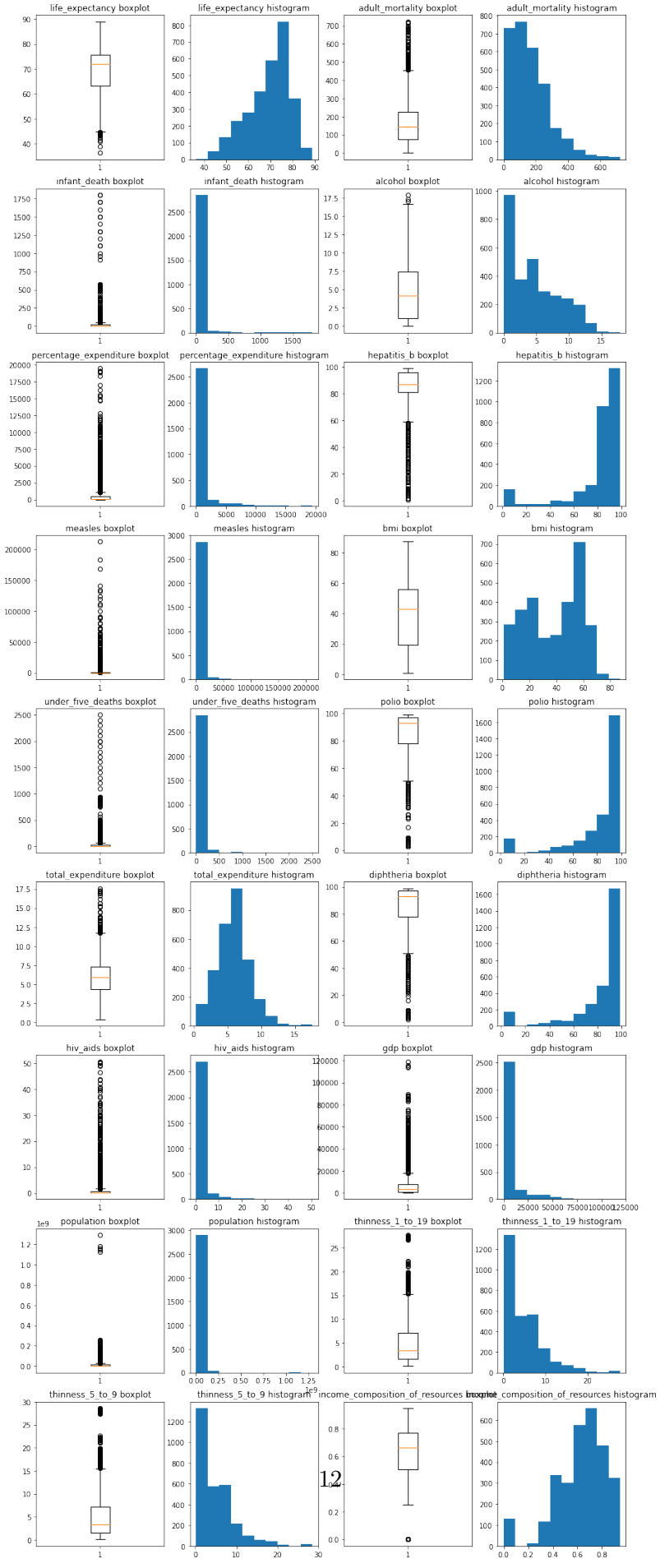
[20]:
```
<pandas.io.formats.style.Styler at 0x7fb145779ac0>
```

Outliers

[21]:
```
cont_vars = list(df.columns)[3:]
def outliers_visual(data):
    plt.figure(figsize=(15, 40))
    i = 0
    for col in cont_vars:
        i += 1
        plt.subplot(9, 4, i)
        plt.boxplot(data[col])
        plt.title('{} boxplot'.format(col))
        i += 1
        plt.subplot(9, 4, i)
        plt.hist(data[col])
        plt.title('{} histogram'.format(col))
    plt.show()
outliers_visual(df)
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Input In [21], in <cell line: 15>()
     13         plt.title('{} histogram'.format(col))
     14     plt.show()
---> 15 outliers_visual(df)

Input In [21], in outliers_visual(data)
      5 for col in cont_vars:
      6     i += 1
----> 7     plt.subplot(9, 4, i)
      8     plt.boxplot(data[col])
      9     plt.title('{} boxplot'.format(col))

File ~/opt/anaconda3/lib/python3.9/site-packages/matplotlib/pyplot.py:1268, in␣
 ↪subplot(*args, **kwargs)
   1265 fig = gcf()
   1267 # First, search for an existing subplot with a matching spec.
-> 1268 key = SubplotSpec._from_subplot_args(fig, args)
   1270 for ax in fig.axes:
   1271     # if we found an axes at the position sort out if we can re-use it
   1272     if hasattr(ax, 'get_subplotspec') and ax.get_subplotspec() == key:
   1273         # if the user passed no kwargs, re-use

File ~/opt/anaconda3/lib/python3.9/site-packages/matplotlib/gridspec.py:608, in␣
 ↪SubplotSpec._from_subplot_args(figure, args)
    606 else:
    607     if not isinstance(num, Integral) or num < 1 or num > rows*cols:
--> 608         raise ValueError(
    609             f"num must be 1 <= num <= {rows*cols}, not {num!r}")
    610     i = j = num
```

```
    611 return gs[i-1:j]

ValueError: num must be 1 <= num <= 36, not 37
```


life_expectancy boxplot
life_expectancy histogram
adult_mortality boxplot
adult_mortality histogram
infant_death boxplot
infant_death histogram
alcohol boxplot
alcohol histogram
percentage_expenditure boxplot
percentage_expenditure histogram
hepatitis_b boxplot
hepatitis_b histogram
measles boxplot
measles histogram
bmi boxplot
bmi histogram
under_five_deaths boxplot
under_five_deaths histogram
polio boxplot
polio histogram
total_expenditure boxplot
total_expenditure histogram
diphtheria boxplot
diphtheria histogram
hiv_aids boxplot
hiv_aids histogram
gdp boxplot
gdp histogram
population boxplot
population histogram
thinness_1_to_19 boxplot
thinness_1_to_19 histogram
thinness_5_to_9 boxplot
thinness_5_to_9 histogram
income_composition_of_resources boxplot
income_composition_of_resources histogram

Visually, it is plain to see that there are a number of outliers for all of these variables - including the target variable, life expectancy.

Uisng Tukey's method below - outliers being considered anything outside of 1.5 times the IQR

[22]:
```
def outlier_count(col, data=df):
    print(15*'-' + col + 15*'-')
    q75, q25 = np.percentile(data[col], [75, 25])
    iqr = q75 - q25
    min_val = q25 - (iqr*1.5)
    max_val = q75 + (iqr*1.5)
    outlier_count = len(np.where((data[col] > max_val) | (data[col] <␣
 ↪min_val))[0])
    outlier_percent = round(outlier_count/len(data[col])*100, 2)
    print('Number of outliers: {}'.format(outlier_count))
    print('Percent of data that is outlier: {}%'.format(outlier_percent))
```

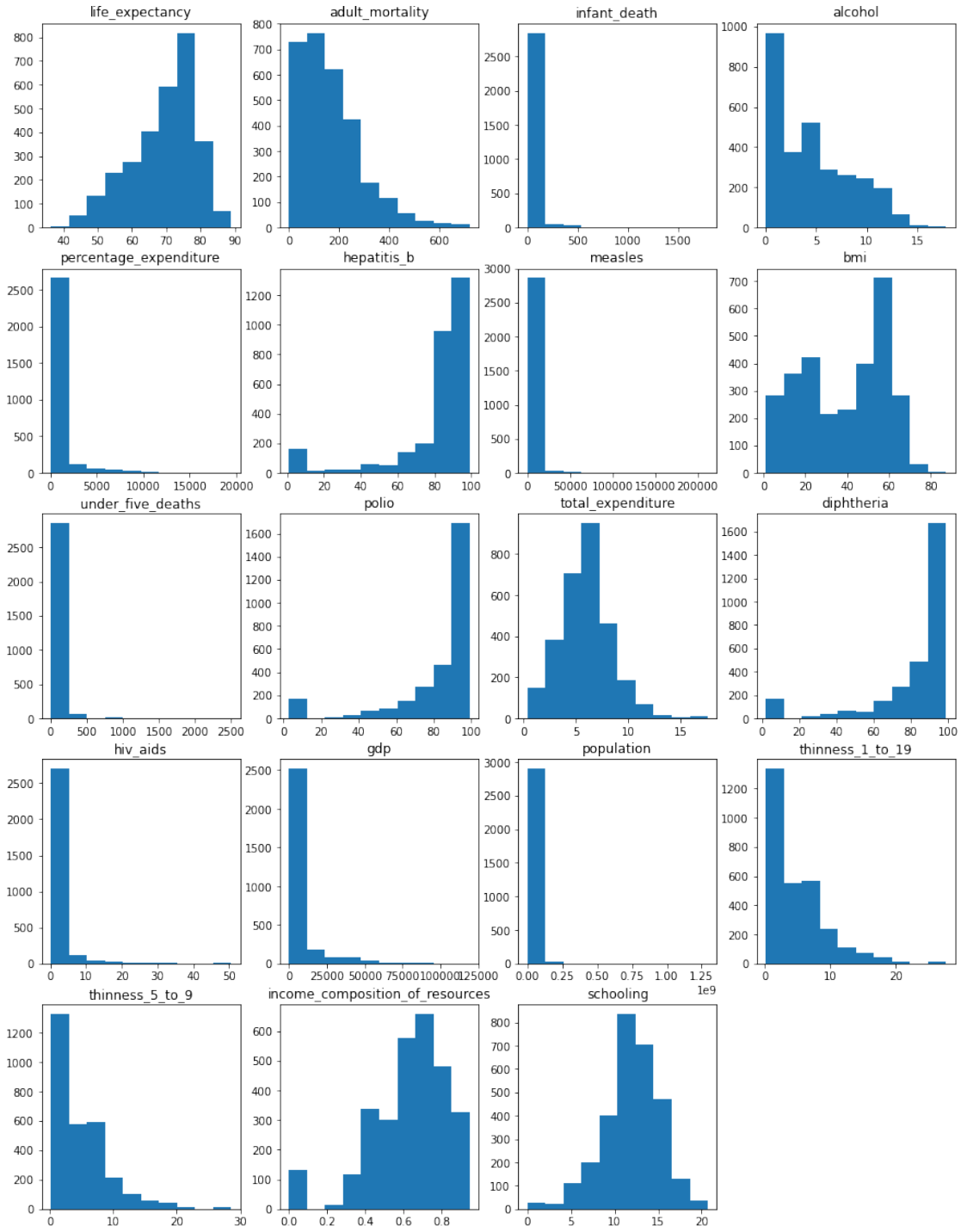
[23]:
```
for col in cont_vars:
    outlier_count(col)
```

```
---------------life_expectancy---------------
Number of outliers: 17
Percent of data that is outlier: 0.58%
---------------adult_mortality---------------
Number of outliers: 86
Percent of data that is outlier: 2.93%
---------------infant_death---------------
Number of outliers: 315
Percent of data that is outlier: 10.72%
---------------alcohol---------------
Number of outliers: 3
Percent of data that is outlier: 0.1%
---------------percentage_expenditure---------------
Number of outliers: 389
Percent of data that is outlier: 13.24%
---------------hepatitis_b---------------
Number of outliers: 316
Percent of data that is outlier: 10.76%
---------------measles---------------
Number of outliers: 542
Percent of data that is outlier: 18.45%
---------------bmi---------------
Number of outliers: 0
Percent of data that is outlier: 0.0%
---------------under_five_deaths---------------
Number of outliers: 394
```

```
Percent of data that is outlier: 13.41%
---------------polio---------------
Number of outliers: 279
Percent of data that is outlier: 9.5%
---------------total_expenditure---------------
Number of outliers: 51
Percent of data that is outlier: 1.74%
---------------diphtheria---------------
Number of outliers: 298
Percent of data that is outlier: 10.14%
---------------hiv_aids---------------
Number of outliers: 542
Percent of data that is outlier: 18.45%
---------------gdp---------------
Number of outliers: 300
Percent of data that is outlier: 10.21%
---------------population---------------
Number of outliers: 194
Percent of data that is outlier: 6.6%
---------------thinness_1_to_19---------------
Number of outliers: 100
Percent of data that is outlier: 3.4%
---------------thinness_5_to_9---------------
Number of outliers: 99
Percent of data that is outlier: 3.37%
---------------income_composition_of_resources---------------
Number of outliers: 130
Percent of data that is outlier: 4.42%
---------------schooling---------------
Number of outliers: 77
Percent of data that is outlier: 2.62%
```

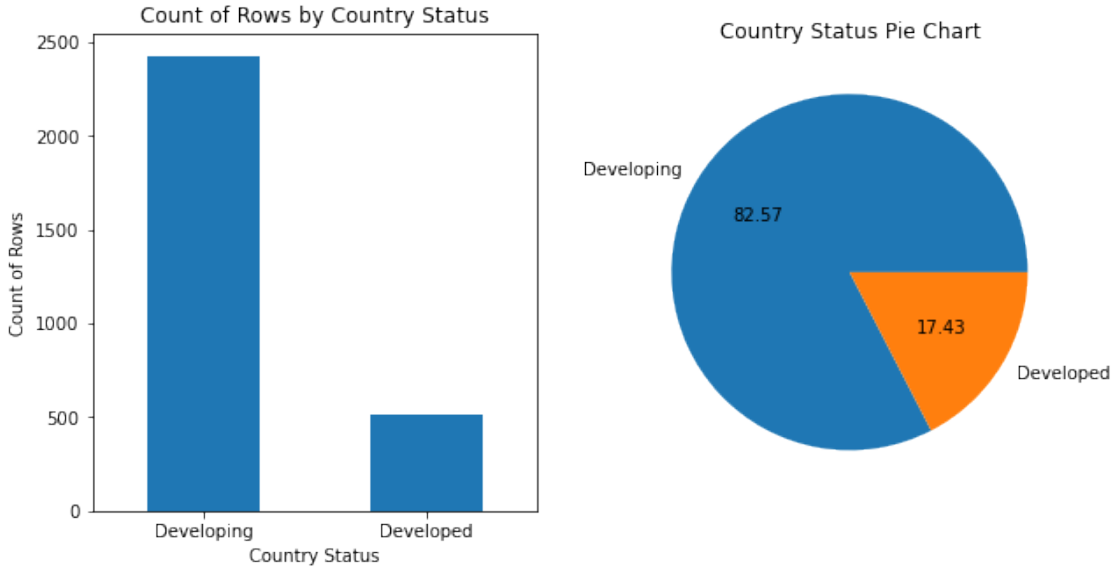
Data Viz

[24]:
```
# Visual Distributions
plt.figure(figsize=(15, 20))
for i, col in enumerate(cont_vars, 1):
    plt.subplot(5, 4, i)
    plt.hist(df[col])
    plt.title(col)
```



[25]:
```
#. Values of rows for status
plt.figure(figsize=(10, 5))
plt.subplot(121)
df.status.value_counts().plot(kind='bar')
```

```
plt.title('Count of Rows by Country Status')
plt.xlabel('Country Status')
plt.ylabel('Count of Rows')
plt.xticks(rotation=0)

plt.subplot(122)
df.status.value_counts().plot(kind='pie', autopct='%.2f')
plt.ylabel('')
plt.title('Country Status Pie Chart')

plt.show()
```

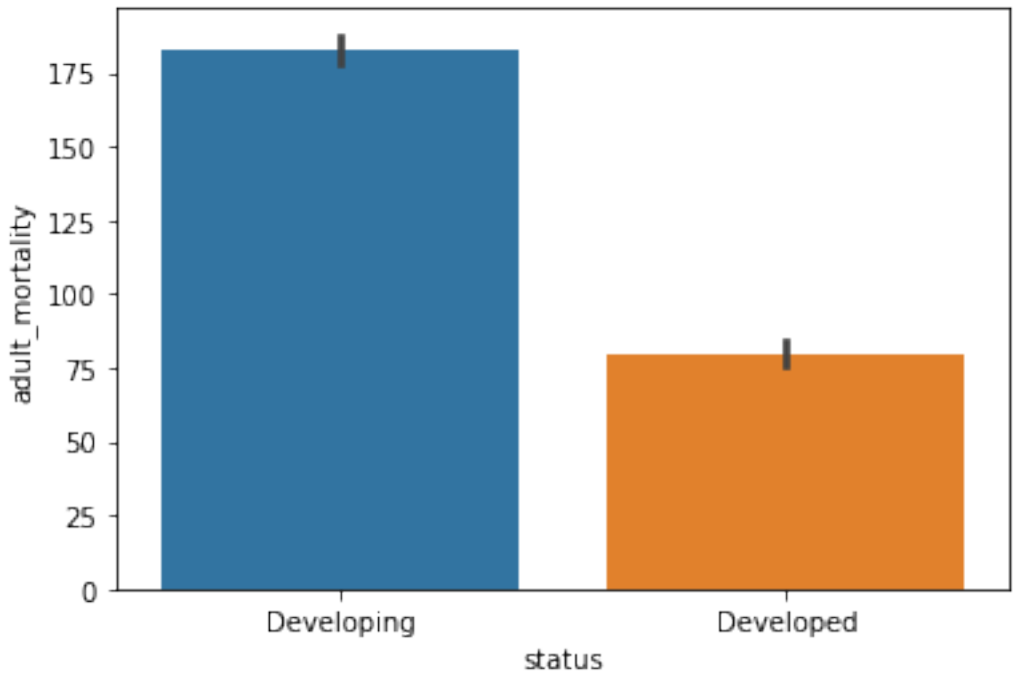


The above displays that the majority of our data comes from countries listed as 'Developing' - 82.57% to be exact. It is likely that any model used will more accurately depict results for 'Developing' countries over 'Developed' countries as the majority of the data lies within countries that are 'Developing' rather than 'Developed'.

[26]:
```
#Adult mortality
sns.barplot(df["status"],df['adult_mortality'])
```

```
/Users/polina/opt/anaconda3/lib/python3.9/site-
packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. 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.
  warnings.warn(
```

[26]:
```
<AxesSubplot:xlabel='status', ylabel='adult_mortality'>
```



[27]:
```
#Distribution of Life Expectancy according to the age
fig = px.histogram(df, x = 'life_expectancy', template = 'plotly_dark')
fig.show()
```

[28]:
```
#Comparing the life expectancy of Developing and Developed Countries
fig = px.violin(df, x= 'status', y= 'life_expectancy',
                color = 'status',template = 'plotly_dark', box =␣
 ↪True,title='Life Expectancy on the Basis of Country Status')
fig.show()
```

[29]:
```
#Country Wise Life Expectancy over the years
fig = px.line((df.sort_values(by = 'year')), x = 'year', y = 'life_expectancy',
    animation_frame= 'country',template = 'plotly_dark',␣
 ↪animation_group='year',color='country',
    markers=True,title='Country Wise Life Expectancy over the years')
fig.show()
```

[30]:
```
country_df = px.data.gapminder()
country_df.tail()
```

[30]:

	country	continent	year	lifeExp	pop	gdpPercap	iso_alpha	\
1699	Zimbabwe	Africa	1987	62.351	9216418	706.157306	ZWE	
1700	Zimbabwe	Africa	1992	60.377	10704340	693.420786	ZWE	
1701	Zimbabwe	Africa	1997	46.809	11404948	792.449960	ZWE	

```
1702  Zimbabwe    Africa  2002   39.989  11926563  672.038623       ZWE
1703  Zimbabwe    Africa  2007   43.487  12311143  469.709298       ZWE

      iso_num
1699      716
1700      716
1701      716
1702      716
1703      716
```

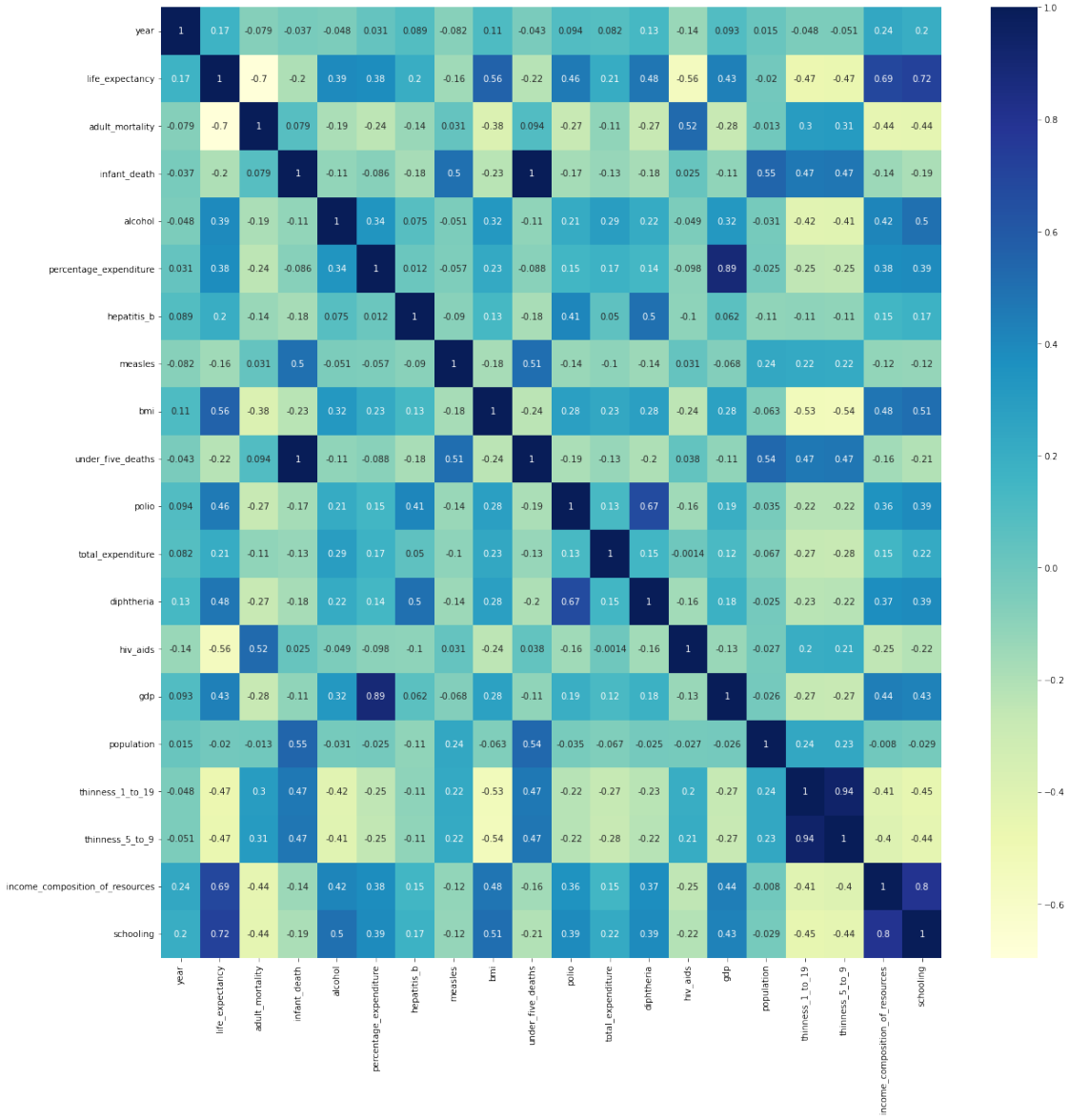
[31]:
```
#Life Expectancy over the World Map
map_fig = px.scatter_geo(country_df,locations = 'iso_alpha', projection =␣
 ↪'orthographic',
                         opacity = 0.8, color = 'country', hover_name =␣
 ↪'country',
                         hover_data = ['lifeExp', 'year'],template =␣
 ↪'plotly_dark',title = 'Life Expectancy over the World Map')
map_fig.show()
```

[32]:
```
# Life Expectancy versus the adult Mortality in different countries every year¶
px.scatter(df, x = 'life_expectancy', y = 'adult_mortality',
           color = 'country', template = 'plotly_dark', size =␣
 ↪'life_expectancy',opacity = 0.6,
           title = '<b>Life Expectancy Vs Adult Mortality in Countries')
```

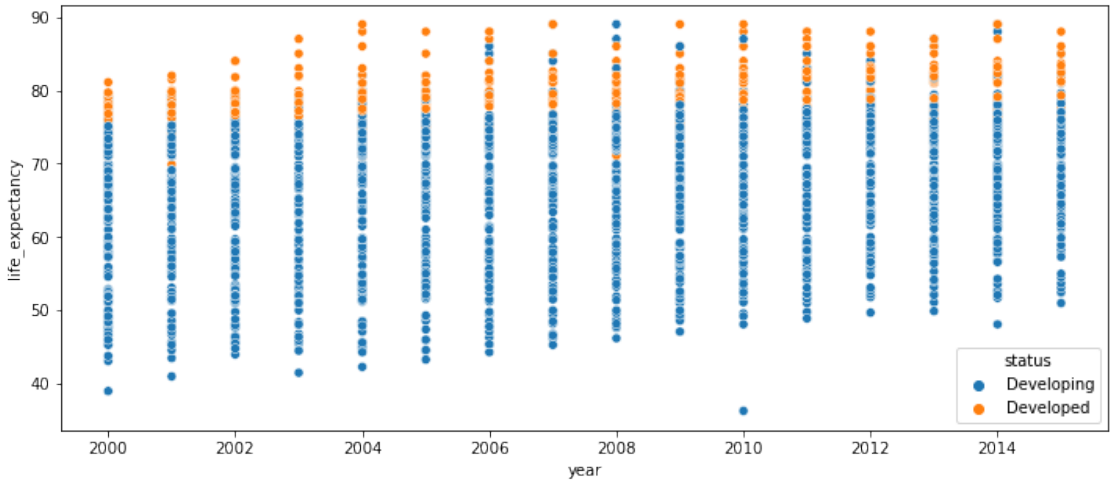
[33]:
```
#Life Expectancy Versus GDP of Counntries all over the World¶
px.scatter(df.sort_values(by='year'), x = 'life_expectancy', y = 'gdp', color =␣
 ↪'country',
          size = 'year',animation_frame = 'year', animation_group =␣
 ↪'country',template = 'plotly_dark',
           title = '<b>Life Expectancy Vs GDP in Countries')
```

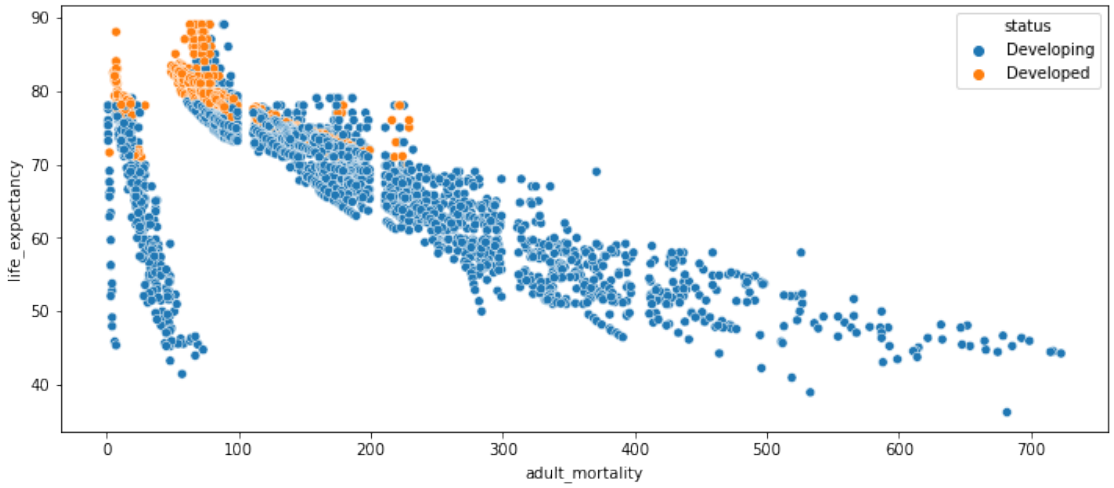
[34]:
```
# country and the sum population
fig=px.histogram(df,x='country',y = 'population', template='seaborn')
fig.show()
```

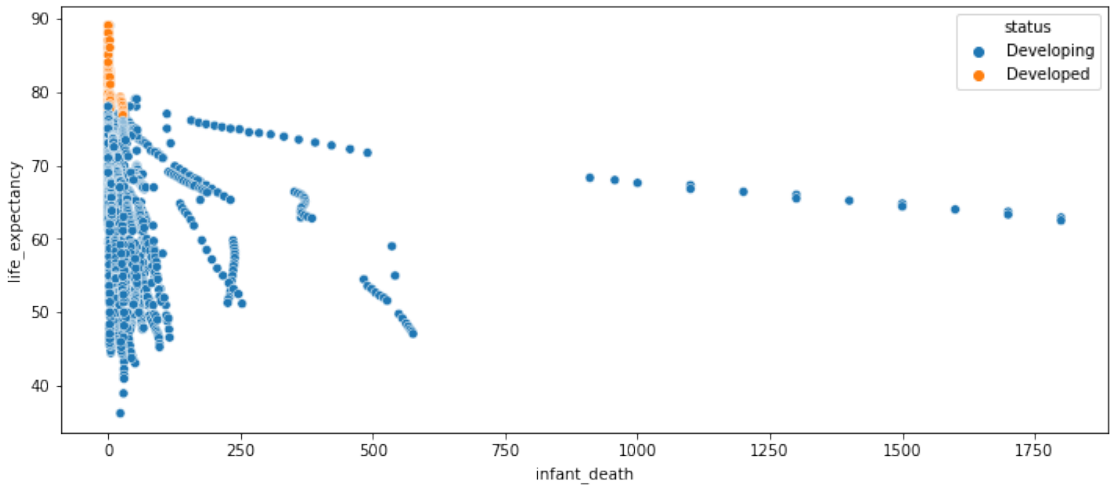
[35]:
```
#correlation plot
plt.figure(figsize=(20,20))
sns.heatmap(df.corr(),annot = True,cmap = "YlGnBu")
plt.show()
```

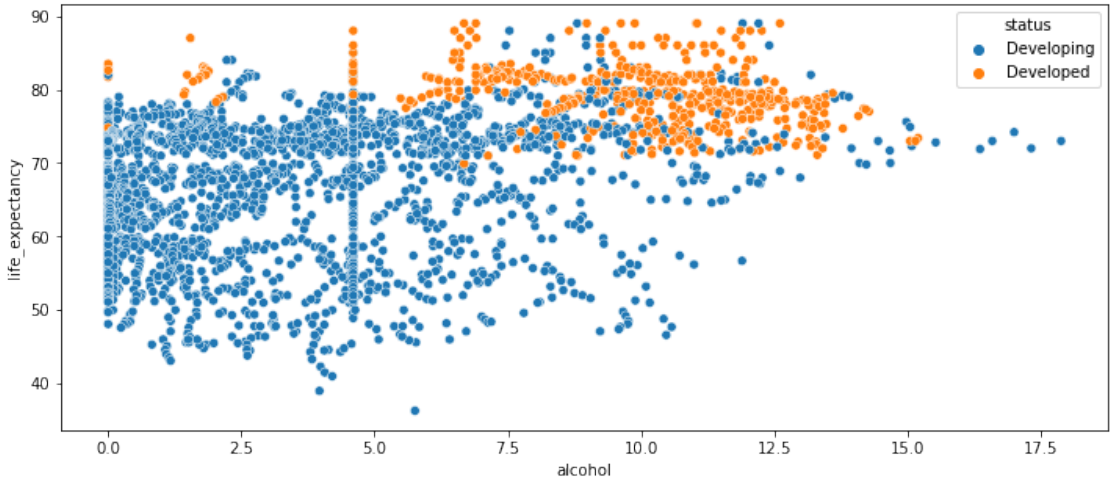


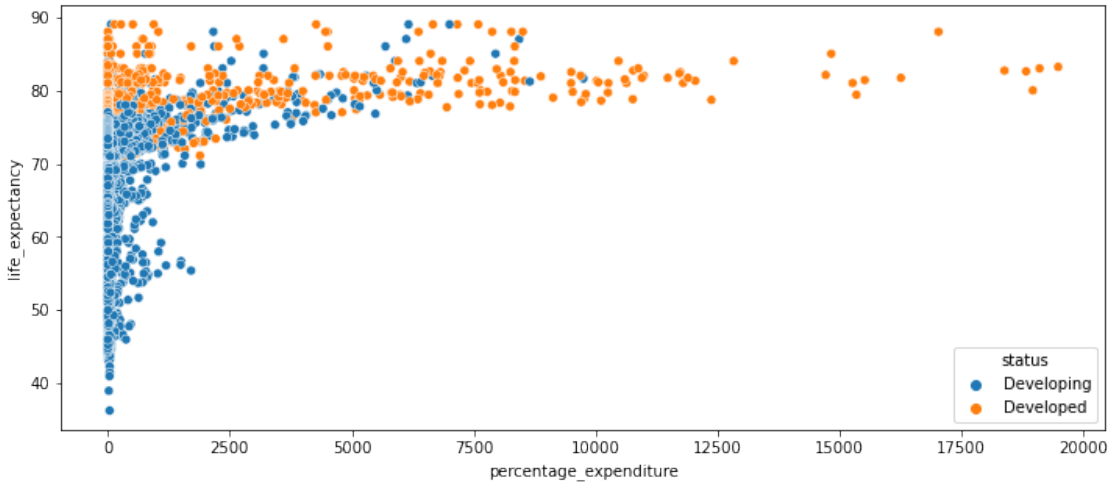
[36]:
```
# plot by. status
y = df["life_expectancy"]
df_clean2 = df.drop("life_expectancy",axis=1)

for feature in df_clean2.select_dtypes(exclude="O").columns:
    plt.figure(figsize=(12,5))
    sns.scatterplot(x=df_clean2[feature],y=y,hue=df_clean2["status"])
```

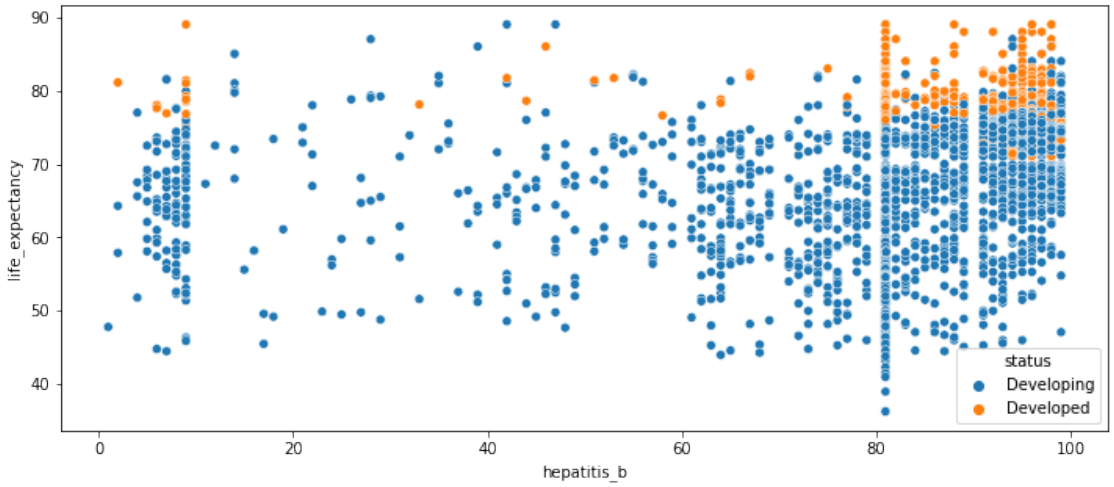

life_expectancy
year
status
Developing
Developed

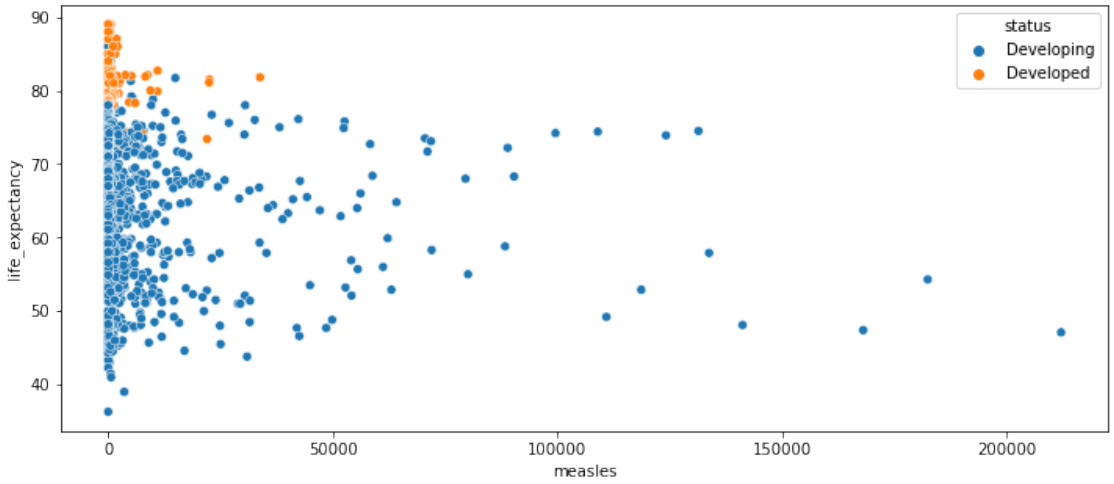

life_expectancy
adult_mortality
status
Developing
Developed

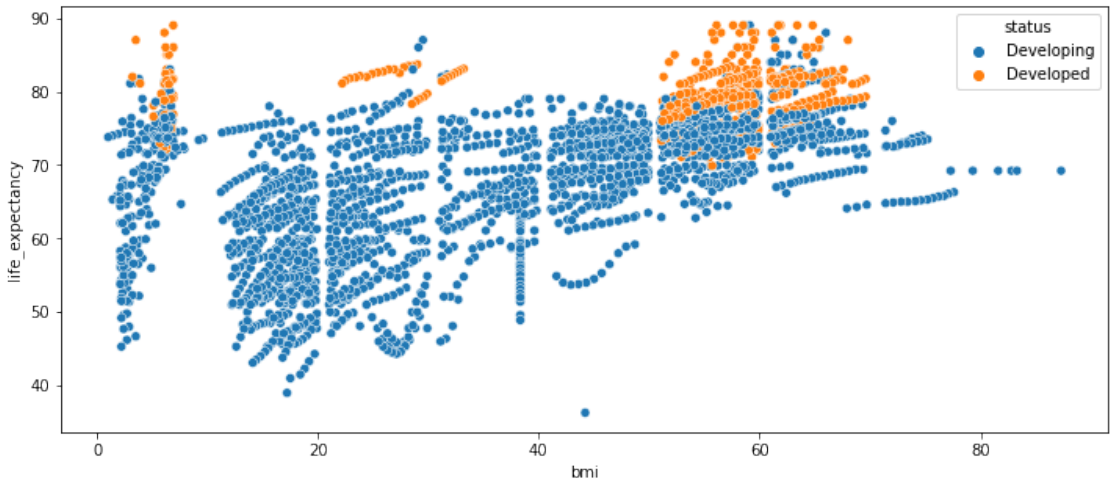

life_expectancy
infant_death
status
Developing
Developed

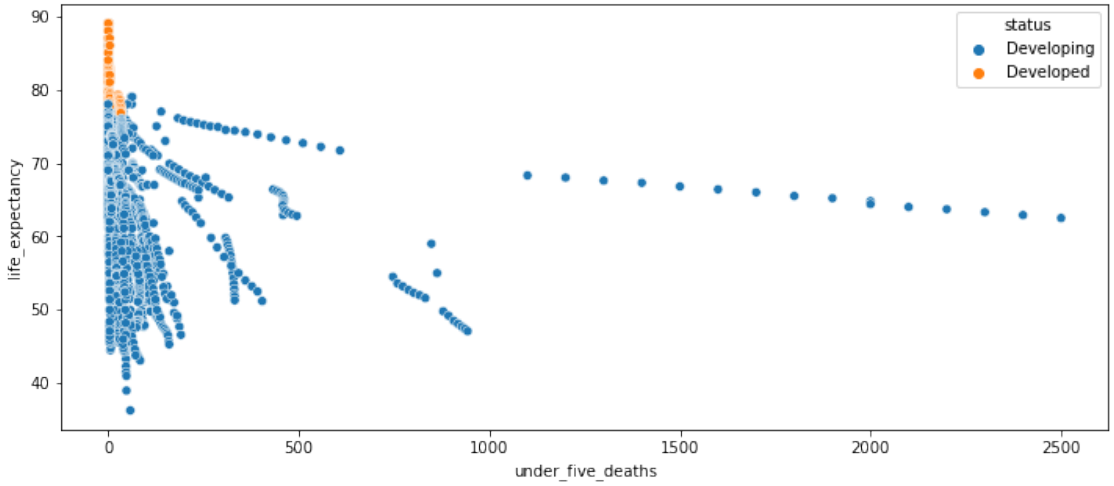

status
Developing
Developed
life_expectancy
alcohol
90
80
70
60
50
40
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

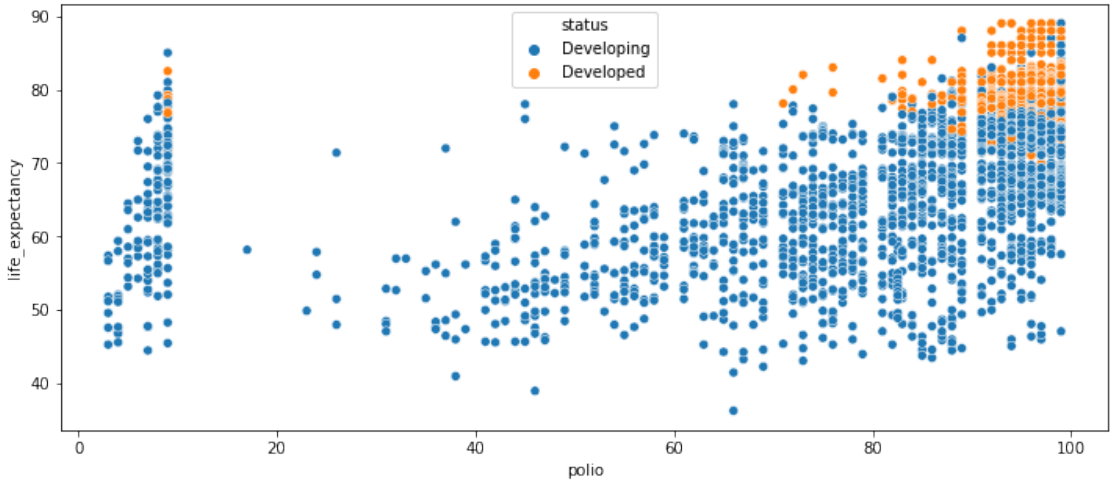

status
Developing
Developed
life_expectancy
percentage_expenditure
90
80
70
60
50
40
0
2500
5000
7500
10000
12500
15000
17500
20000

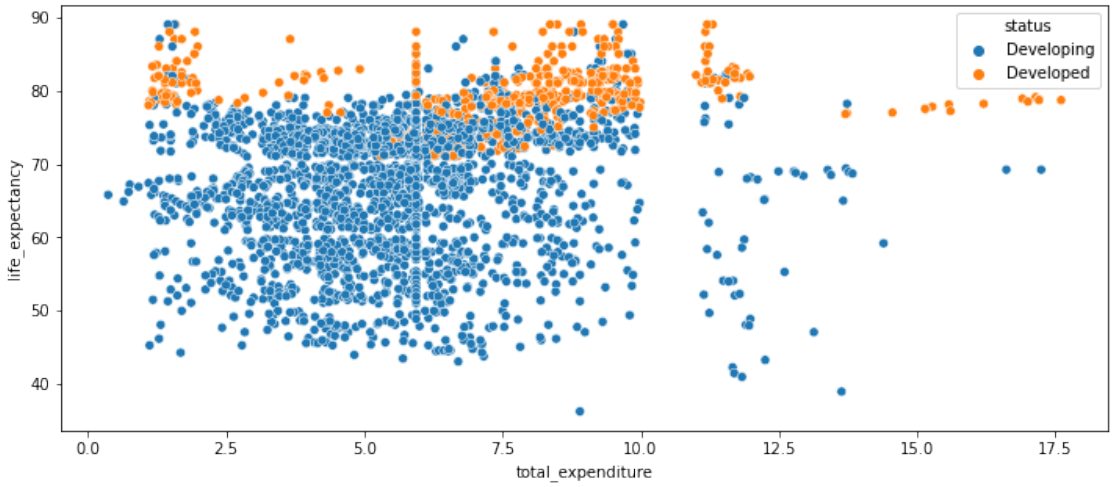

life_expectancy
hepatitis_b
status
Developing
Developed

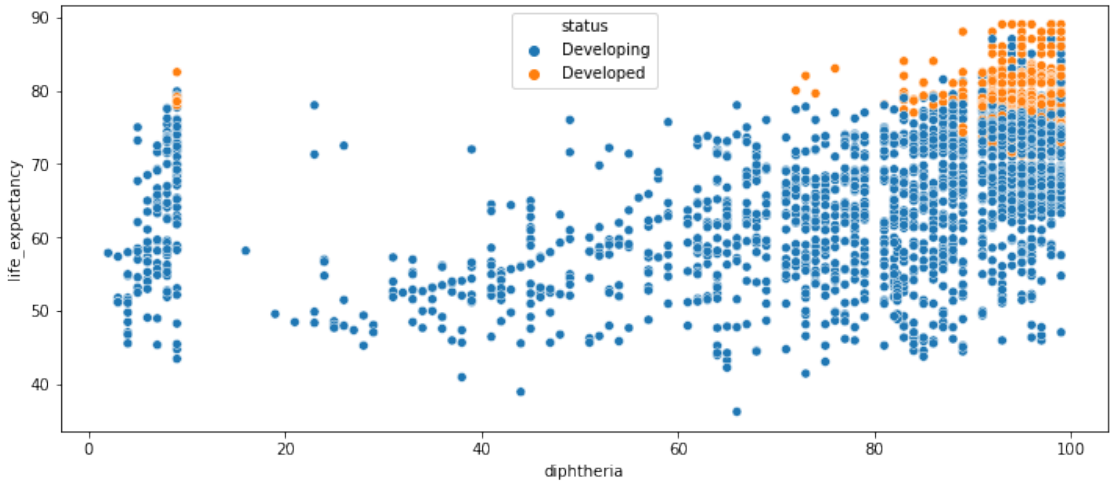

life_expectancy
measles
status
Developing
Developed

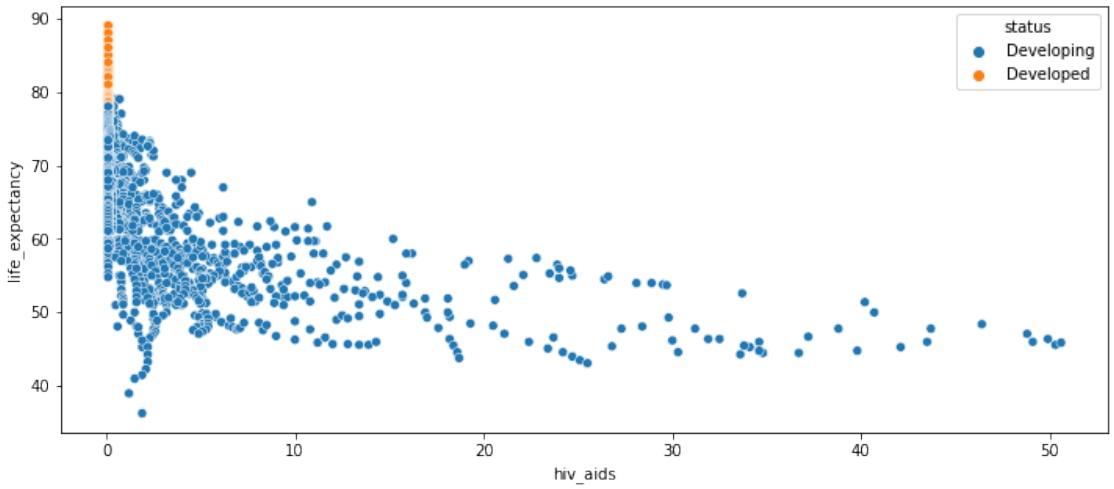

life_expectancy
bmi
status
Developing
Developed

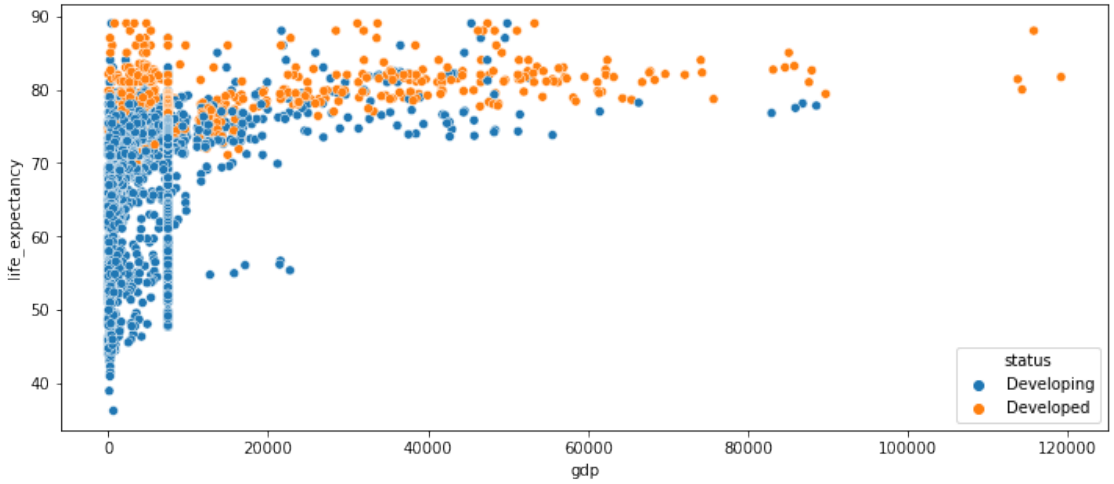

status
Developing
Developed
life_expectancy
under_five_deaths
90
80
70
60
50
40
0
500
1000
1500
2000
2500

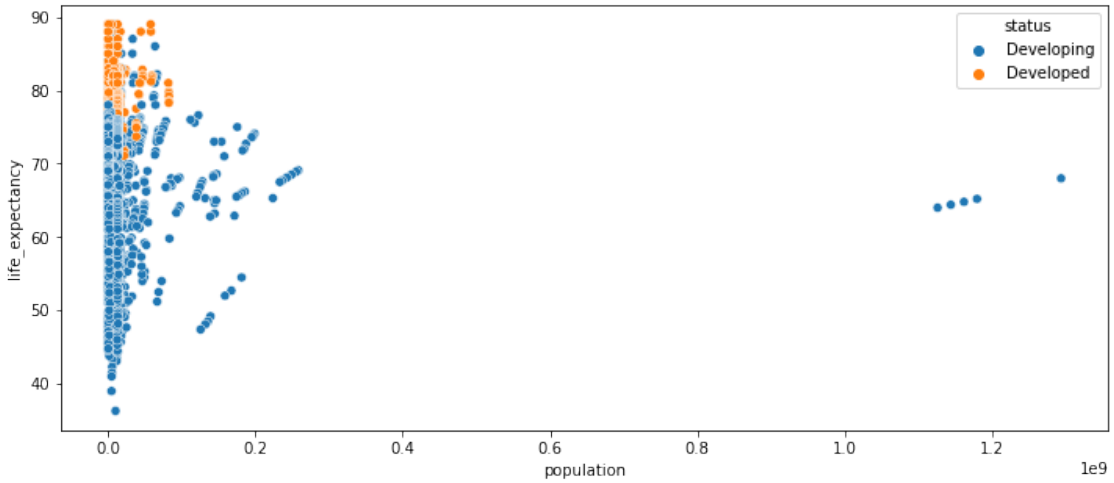

status
Developing
Developed
life_expectancy
polio
90
80
70
60
50
40
0
20
40
60
80
100

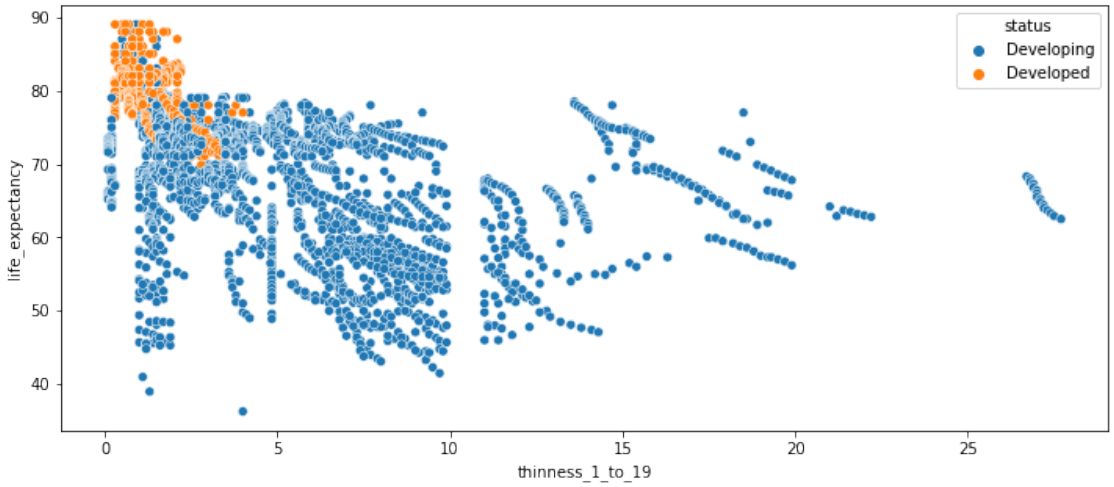

status
Developing
Developed
life_expectancy
total_expenditure
90
80
70
60
50
40
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

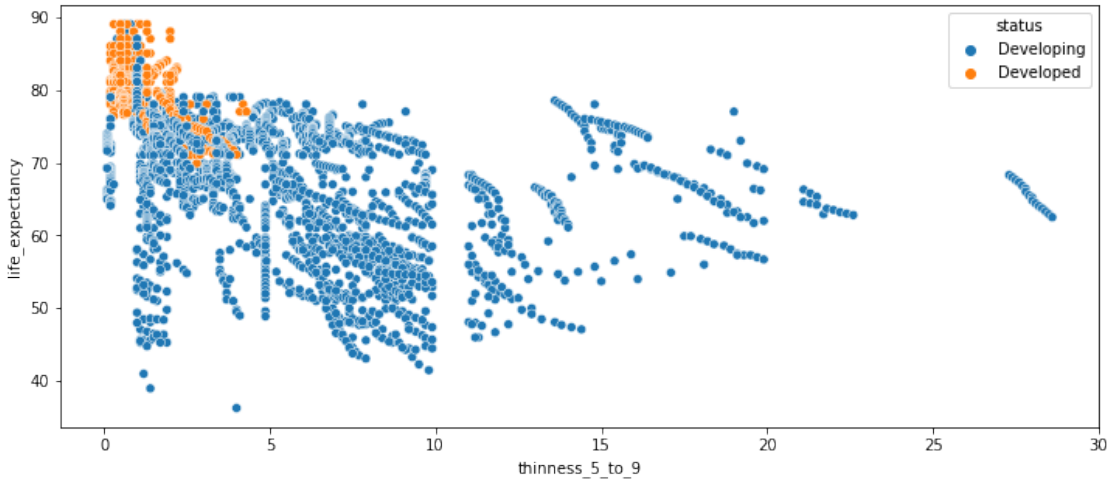

status
Developing
Developed
life_expectancy
diphtheria
90
80
70
60
50
40
0
20
40
60
80
100

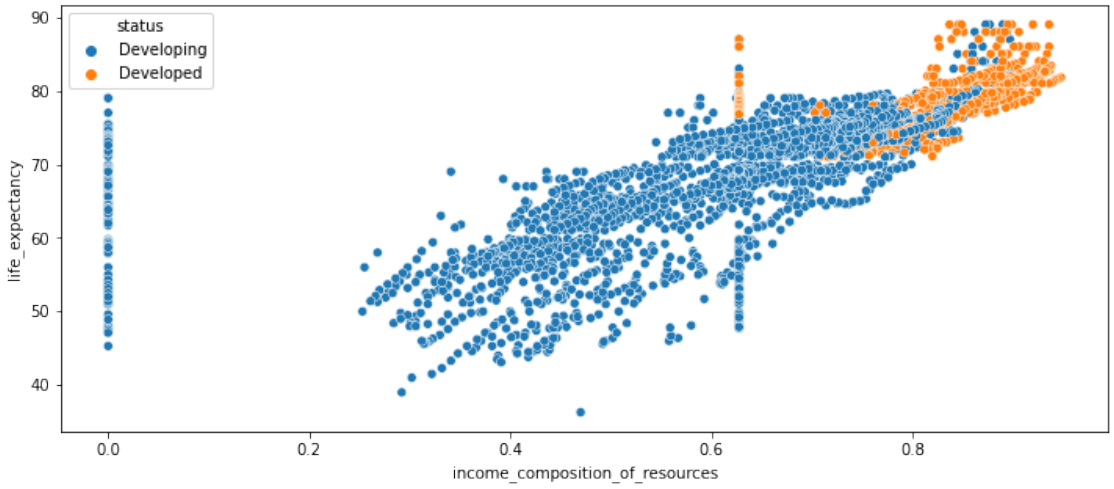

status
Developing
Developed
life_expectancy
hiv_aids
90
80
70
60
50
40
0
10
20
30
40
50

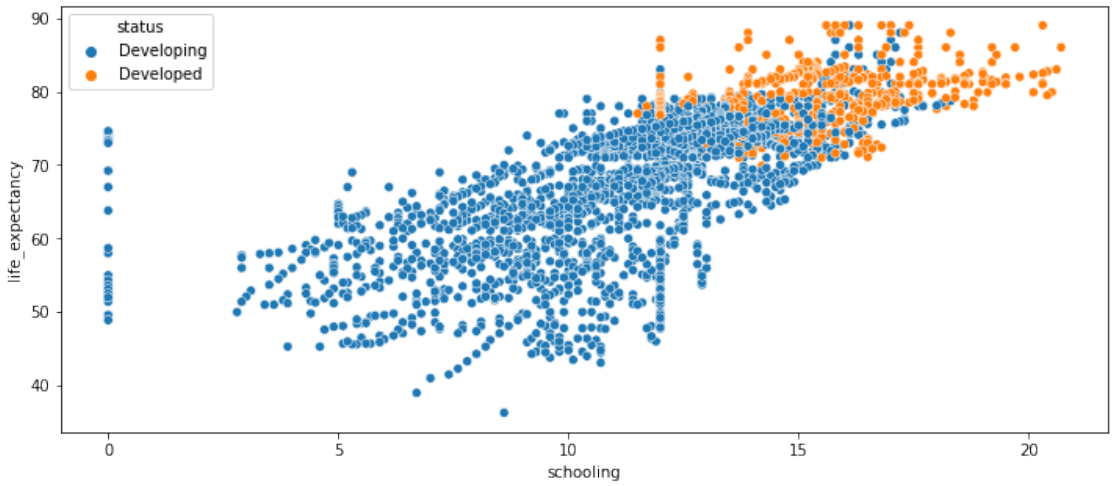

life_expectancy
gdp
status
Developing
Developed
90
80
70
60
50
40
0
20000
40000
60000
80000
100000
120000


life_expectancy
population
1e9
status
Developing
Developed
90
80
70
60
50
40
0.0
0.2
0.4
0.6
0.8
1.0
1.2


status
Developing
Developed
life_expectancy
thinness_1_to_19


status
Developing
Developed
life_expectancy
thinness_5_to_9


status
Developing
Developed
life_expectancy
income_composition_of_resources



[94]:
```
# Let's made an interactive plot with the help of plotly
numerical_features = df.copy()
```

[95]:
```
countries = numerical_features["country"].unique()
def make_scatter_plot_country_wise(feature):
    first_title = countries[0]
    traces = []
    buttons = []
    frame = []

    for index,country in enumerate(countries):
        visible = [False] * len(countries)
        visible[index] = True
        name = country
        # Get the dataFrame curresponding to that country
        country_data = numerical_features.query('country == @country')

        traces.append(
            px.scatter(country_data, x=feature, y="life_expectancy",␣
 ↪color="year").update_traces(visible=True if index==0 else False).data[0]
        )

        buttons.append(dict(label=name,
                            method="update",
                            args=[{"visible":visible}, {"title":f"{name}"}]))

    fig = go.Figure(data=traces)
    fig.update_layout( xaxis_title=f"<b>{feature}</b>",
```

```
                        yaxis_title="<b>life_expectancy</b>",
                        legend_title="Year",
                        updatemenus=[go.layout.Updatemenu(
                            active=0,
                            buttons=buttons
                            )
                        ])
    fig.update_traces(marker_size=40)

    fig.update_layout(title=f"<b>{feature}</b>")
    fig.show()
```

[96]:
```
numerical_features.columns.values
```

[96]:
```
array(['country', 'year', 'status', 'life_expectancy', 'adult_mortality',
       'infant_death', 'alcohol', 'percentage_expenditure', 'hepatitis_b',
       'measles', 'bmi', 'under_five_deaths', 'polio',
       'total_expenditure', 'diphtheria', 'hiv_aids', 'gdp', 'population',
       'thinness_1_to_19', 'thinness_5_to_9',
       'income_composition_of_resources', 'schooling'], dtype=object)
```

[97]:
```
import plotly.graph_objs as go
```

[98]:
```
for i in numerical_features.columns.values:
    if i == "Country" or i == "Status" or i == "Life expectancy ":
        continue
    make_scatter_plot_country_wise(i)
```

[104]:
```
# worldmap plotly
from plotly.offline import init_notebook_mode, iplot
count = [ dict(
        # set the map type is choropleth
        type = 'choropleth',
        locations = df['country'],
        locationmode='country names',
        z = df['life_expectancy'],
        text = df['country'],
        colorscale = 'Viridis',
        autocolorscale = False,
        reversescale = True,
        # set the plotly gragh color
        marker = dict(
            line = dict (
                color = 'rgb(180,180,180)',
                width = 0.5
            ) ),
        # add a color bar
```

```
        colorbar = dict(
            autotick =False,
            title = 'Life Expectancy Country-based'),
      ) ]
# create layout for gragh
layout = dict(
    title = 'Life Expectancy across the Global',
    #
    geo = dict(
        showframe = True,
        showcoastlines = True,
        projection = dict(
            type = 'Mercator'
        )
    )
)
# prepare the fig parameter
fig = dict( data=count, layout=layout )
iplot( fig, validate=False, filename='d3-world-map' )
```

Dashboard with pandas-profiling

[ ]:
```
pip install pandas-profiling
```

[37]:
```
import pandas_profiling
report = df.profile_report(
    sort=None, html={"style": {"full_width": True}}, progress_bar=False
)
report
```

```
<IPython.core.display.HTML object>
```

[37]:

Linear Regression

[38]:
```
df_status = df.replace({"Developed":1,"Developing":0})
```

[40]:
```
#check status
df_status['status']
df_status
```

[40]:

	country	year	status	life_expectancy	adult_mortality	\
0	Afghanistan	2015	0	65.0	263.0	
1	Afghanistan	2014	0	59.9	271.0	
2	Afghanistan	2013	0	59.9	268.0	
3	Afghanistan	2012	0	59.5	272.0	
4	Afghanistan	2011	0	59.2	275.0	
…	…	…	…	…	…	

```
2933     Zimbabwe  2004       0             44.3           723.0
2934     Zimbabwe  2003       0             44.5           715.0
2935     Zimbabwe  2002       0             44.8            73.0
2936     Zimbabwe  2001       0             45.3           686.0
2937     Zimbabwe  2000       0             46.0           665.0

      infant_death  alcohol  percentage_expenditure  hepatitis_b  measles  \
0               62     0.01               71.279624         65.0     1154
1               64     0.01               73.523582         62.0      492
2               66     0.01               73.219243         64.0      430
3               69     0.01               78.184215         67.0     2787
4               71     0.01                7.097109         68.0     3013
…              …      …                   …               …       …
2933            27     4.36                0.000000         68.0       31
2934            26     4.06                0.000000          7.0      998
2935            25     4.43                0.000000         73.0      304
2936            25     1.72                0.000000         76.0      529
2937            24     1.68                0.000000         79.0     1483

      …  polio  total_expenditure  diphtheria  hiv_aids         gdp  \
0     …    6.0               8.16        65.0       0.1  584.259210
1     …   58.0               8.18        62.0       0.1  612.696514
2     …   62.0               8.13        64.0       0.1  631.744976
3     …   67.0               8.52        67.0       0.1  669.959000
4     …   68.0               7.87        68.0       0.1   63.537231
…   …    …                 …          …         …          …
2933  …   67.0               7.13        65.0      33.6  454.366654
2934  …    7.0               6.52        68.0      36.7  453.351155
2935  …   73.0               6.53        71.0      39.8   57.348340
2936  …   76.0               6.16        75.0      42.1  548.587312
2937  …   78.0               7.10        78.0      43.5  547.358878

      population  thinness_1_to_19  thinness_5_to_9  \
0     33736494.0              17.2             17.3
1       327582.0              17.5             17.5
2     31731688.0              17.7             17.7
3      3696958.0              17.9             18.0
4      2978599.0              18.2             18.2
…          …                 …               …
2933  12777511.0               9.4              9.4
2934  12633897.0               9.8              9.9
2935    125525.0               1.2              1.3
2936  12366165.0               1.6              1.7
2937  12222251.0              11.0             11.2

      income_composition_of_resources  schooling
0                               0.479       10.1
```

```
1                                 0.476       10.0
2                                 0.470        9.9
3                                 0.463        9.8
4                                 0.454        9.5
…                                 …          …
2933                              0.407        9.2
2934                              0.418        9.5
2935                              0.427       10.0
2936                              0.427        9.8
2937                              0.434        9.8

[2938 rows x 22 columns]
```

[41]:
```
from sklearn.linear_model import LinearRegression

Y = df_status["life_expectancy"]
X = df_status.drop(["life_expectancy","country"], axis=1)
lrm = LinearRegression()
lrm.fit(X,Y)
```

[41]:
```
LinearRegression()
```

[42]:
```
import statsmodels.api as sm

X = sm.add_constant(X)
results = sm.OLS(Y, X).fit()
results.summary()
```

[42]:
```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results
==============================================================================
Dep. Variable:        life_expectancy   R-squared:                       0.820
Model:                            OLS   Adj. R-squared:                  0.819
Method:                 Least Squares   F-statistic:                     663.3
Date:                Mon, 12 Dec 2022   Prob (F-statistic):               0.00
Time:                        17:58:51   Log-Likelihood:                -8268.0
No. Observations:                2938   AIC:                         1.658e+04
Df Residuals:                    2917   BIC:                         1.670e+04
Df Model:                          20
Covariance Type:            nonrobust
==============================================================================
                                 coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
------------------
```

```
const                            73.4394     34.723      2.115      0.035
5.356     141.523
year                             -0.0092      0.017     -0.533      0.594
-0.043       0.025
status                            1.5897      0.270      5.886      0.000
1.060       2.119
adult_mortality                  -0.0198      0.001    -24.926      0.000
-0.021      -0.018
infant_death                      0.0998      0.008     11.839      0.000
0.083       0.116
alcohol                           0.0620      0.026      2.381      0.017
0.011       0.113
percentage_expenditure         8.534e-05   8.47e-05      1.008      0.314
-8.07e-05       0.000
hepatitis_b                      -0.0147      0.004     -3.752      0.000
-0.022      -0.007
measles                       -1.96e-05   7.66e-06     -2.558      0.011
-3.46e-05   -4.58e-06
bmi                               0.0444      0.005      8.998      0.000
0.035       0.054
under_five_deaths                -0.0747      0.006    -12.094      0.000
-0.087      -0.063
polio                             0.0285      0.004      6.385      0.000
0.020       0.037
total_expenditure                 0.0661      0.034      1.930      0.054
-0.001       0.133
diphtheria                        0.0402      0.005      8.544      0.000
0.031       0.049
hiv_aids                         -0.4708      0.018    -26.667      0.000
-0.505      -0.436
gdp                            3.347e-05    1.3e-05      2.571      0.010
7.94e-06     5.9e-05
population                     2.751e-10   1.69e-09      0.163      0.871
-3.04e-09    3.59e-09
thinness_1_to_19                 -0.0818      0.050     -1.624      0.105
-0.181       0.017
thinness_5_to_9                   0.0073      0.050      0.147      0.883
-0.090       0.105
income_composition_of_resources   5.7738      0.641      9.003      0.000
4.516       7.031
schooling                         0.6574      0.042     15.693      0.000
0.575       0.740
==============================================================================
Omnibus:                      135.918   Durbin-Watson:                   0.701
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              398.080
Skew:                          -0.175   Prob(JB):                     3.62e-87
Kurtosis:                       4.769   Cond. No.                     2.57e+10
```

```
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.57e+10. This might indicate that there are
strong multicollinearity or other numerical problems.
"""
```

KNN

[43]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.25,␣
 ↪random_state=123)

X_test = sm.add_constant(X_test)
y_preds = results.predict(X_test)
```

[44]:
```
from sklearn.neighbors import KNeighborsRegressor

knn = KNeighborsRegressor()
knn.fit(X_train,y_train)
```

[44]:
```
KNeighborsRegressor()
```

[45]:
```
from sklearn.model_selection import GridSearchCV

knn_parameters = {"n_neighbors":range(1,10),
                  "weights":["uniform","distance"],
                 }

grid_knn = GridSearchCV(estimator=knn,
                        param_grid = knn_parameters,
                        cv = 10)

grid_knn.fit(X, Y)
```

[45]:
```
GridSearchCV(cv=10, estimator=KNeighborsRegressor(),
             param_grid={'n_neighbors': range(1, 10),
                         'weights': ['uniform', 'distance']})
```

[46]:
```
print("Best R-squared score::{}".format(grid_knn.best_score_))
print("Best parameters::\n{}".format(grid_knn.best_params_))
```

```
Best R-squared score::0.00395337491989819
Best parameters::
{'n_neighbors': 9, 'weights': 'uniform'}
```

PCA

PCA is used to preprocess the data to perform K-Means Clustering

[47]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

[48]:
```
df.iloc[:,3:].apply(pd.to_numeric,errors='coerce')
```

[48]:

	life_expectancy	adult_mortality	infant_death	alcohol	\
0	65.0	263.0	62	0.01	
1	59.9	271.0	64	0.01	
2	59.9	268.0	66	0.01	
3	59.5	272.0	69	0.01	
4	59.2	275.0	71	0.01	
…	…	…	…	…	
2933	44.3	723.0	27	4.36	
2934	44.5	715.0	26	4.06	
2935	44.8	73.0	25	4.43	
2936	45.3	686.0	25	1.72	
2937	46.0	665.0	24	1.68	

	percentage_expenditure	hepatitis_b	measles	bmi	under_five_deaths	\
0	71.279624	65.0	1154	19.1	83	
1	73.523582	62.0	492	18.6	86	
2	73.219243	64.0	430	18.1	89	
3	78.184215	67.0	2787	17.6	93	
4	7.097109	68.0	3013	17.2	97	
…	…	…	…	…	…	
2933	0.000000	68.0	31	27.1	42	
2934	0.000000	7.0	998	26.7	41	
2935	0.000000	73.0	304	26.3	40	
2936	0.000000	76.0	529	25.9	39	
2937	0.000000	79.0	1483	25.5	39	

	polio	total_expenditure	diphtheria	hiv_aids	gdp	population	\
0	6.0	8.16	65.0	0.1	584.259210	33736494.0	
1	58.0	8.18	62.0	0.1	612.696514	327582.0	
2	62.0	8.13	64.0	0.1	631.744976	31731688.0	
3	67.0	8.52	67.0	0.1	669.959000	3696958.0	
4	68.0	7.87	68.0	0.1	63.537231	2978599.0	
…	…	…	…	…	…	…	
2933	67.0	7.13	65.0	33.6	454.366654	12777511.0	
2934	7.0	6.52	68.0	36.7	453.351155	12633897.0	
2935	73.0	6.53	71.0	39.8	57.348340	125525.0	
2936	76.0	6.16	75.0	42.1	548.587312	12366165.0	

```
2937   78.0               7.10        78.0      43.5  547.358878  12222251.0

      thinness_1_to_19  thinness_5_to_9  income_composition_of_resources  \
0                 17.2             17.3                            0.479
1                 17.5             17.5                            0.476
2                 17.7             17.7                            0.470
3                 17.9             18.0                            0.463
4                 18.2             18.2                            0.454
…                 …                …                               …
2933               9.4              9.4                            0.407
2934               9.8              9.9                            0.418
2935               1.2              1.3                            0.427
2936               1.6              1.7                            0.427
2937              11.0             11.2                            0.434

      schooling
0          10.1
1          10.0
2           9.9
3           9.8
4           9.5
…           …
2933        9.2
2934        9.5
2935       10.0
2936        9.8
2937        9.8

[2938 rows x 19 columns]
```

[49]:
```
drop_list = ["life_expectancy","country"]
df.drop(drop_list, axis=1 ,inplace=True)
df1 = df.copy()
group = []
for i in df1.columns:
    if (df1[i].dtypes == "object"):
        group.append(i)

#print(group)

lbl_encode = LabelEncoder()
for i in group :
    df1[i]=lbl_encode.fit_transform(df1[[i]])
```

```
/Users/polina/opt/anaconda3/lib/python3.9/site-
packages/sklearn/preprocessing/_label.py:115: DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the
```

shape of y to (n_samples,), for example using ravel().

[50]:
```
scaler = StandardScaler()
scaler.fit(df1)
scaled_df = pd.DataFrame(scaler.transform(df1), columns=df1.columns)
```

[51]:
```
scaled_df.head()
```

[51]:

	year	status	adult_mortality	infant_death	alcohol	percentage_expenditure	hepatitis_b	measles	bmi	under_five_deaths	polio	total_expenditure	diphtheria	hiv_aids	gdp	population	thinness_1_to_19	thinness_5_to_9	income_composition_of_resources	schooling
0	1.621762	0.459399	0.791586	0.268824	-1.172958	-0.335570	-0.705861	-0.110384	-0.964715	0.255359	-3.278638	0.925806	-0.732952	-0.323445	-0.525248	0.389975	2.813130	2.773279	-0.725401	-0.579931
1	1.404986	0.459399	0.856072	0.285786	-1.172958	-0.334441	-0.838704	-0.168124	-0.989810	0.274060	-1.051482	0.934140	-0.859877	-0.323445	-0.523083	-0.230936	2.881408	2.817902	-0.740050	-0.610570
2	1.188210	0.459399	0.831890	0.302749	-1.172958	-0.334594	-0.750142	-0.173531	-1.014905	0.292761	-0.880163	0.913306	-0.775260	-0.323445	-0.521632	0.352715	2.926927	2.862526	-0.769349	-0.641209
3	0.971434	0.459399	0.864132	0.328193	-1.172958	-0.332096	-0.617299	0.032045	-1.040000	0.317696	-0.666013	1.075815	-0.648335	-0.323445	-0.518723	-0.168315	2.972446	2.929461	-0.803531	-0.671847
4	0.754658	0.459399	0.888314	0.345155	-1.172958	-0.367862	-0.573018	0.051757	-1.060076	0.342631	-0.623183	0.804966	-0.606027	-0.323445	-0.564893	-0.181666	3.040724	2.974085	-0.847480	-0.763764

[125]:
```
# The number of dimensions as 3
pca = PCA(n_components=3)
pca.fit(scaled_df)
pca_data = pd.DataFrame(pca.transform(scaled_df), columns=["c1", "c2", "c3"])
```

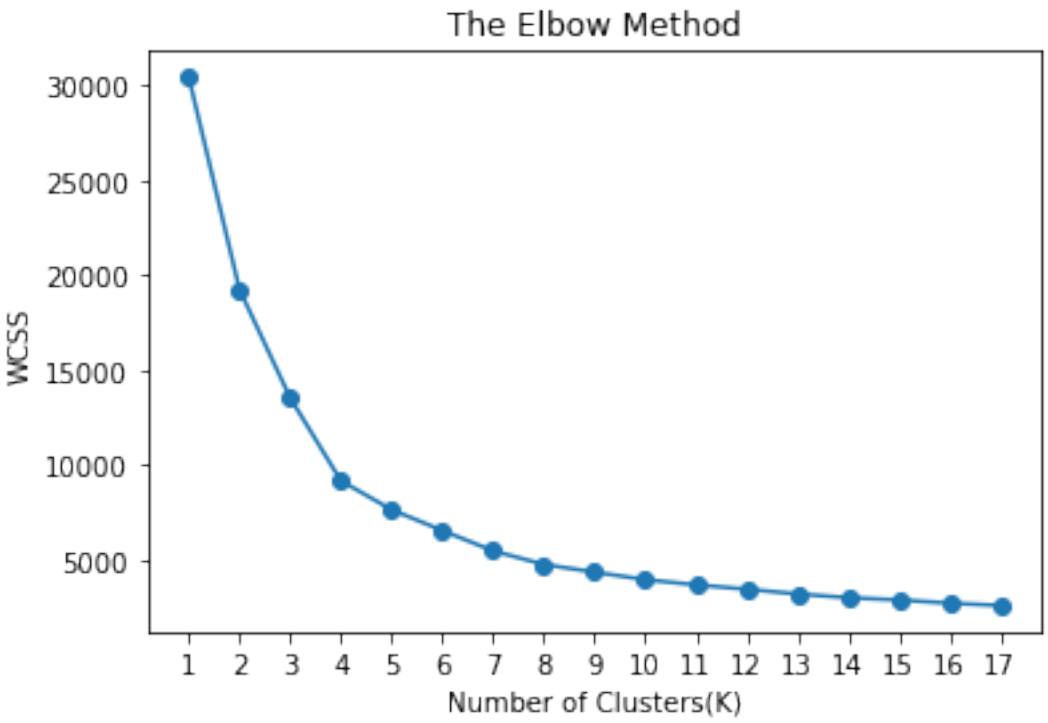
[126]:
```
import plotly.graph_objs as go
x = pca_data["c1"]
y = pca_data["c2"]
z = pca_data["c3"]

fig = go.Figure(data=[go.Scatter3d(
    x=x,y=y,z=z,mode='markers',
    marker=dict(size=6,color=x,opacity=0.8))])

fig.update_layout( title={'text': "3D Plot of Size-Reduced Data",'y':0.9,
        'x':0.5,'xanchor': 'center','yanchor': 'top'},
                  margin=dict(l=200, r=220, b=0, t=0))
fig.show()
```

K Means Clustering using Elbow Method

[55]:
```
from sklearn.cluster import KMeans
```

- Each cluster is formed by calculation and comparing the distance of data point withon a cluster to its center
- Within-Cluster-Sum-of-Squares(WCSS) - to fund the right number of clusters. WCSS is the sum of squares of the distances of each data point in all clusters to their respective centers, and the goal is to minimize the sum. Assume there are n observations in a dataset and we specify n number of clusters, which means k = n; so WCSS turns to 0 since data points themselves become centers and the distance will be 0, in turn this will perform a perfect cluster; but this is almost impossible as we have many clusters as the observations. Thus, we use Elbow point graph to find the optimum value for K by fitting the model in a range of values of K. We randomly initialize the K-Means algorithm for a range of K values and plot it against the WCSS for each K value.

[56]:
```
#https://www.geeksforgeeks.org/elbow-method-for-optimal-value-of-k-in-kmeans/
wcss = []
k = range(1,18)
for i in k:
    model = KMeans(n_clusters=i)
    model.fit(pca_data)
    wcss.append(model.inertia_)

plt.plot(k, wcss, '-o')
plt.title('The Elbow Method')
plt.xlabel('Number of Clusters(K)')
plt.ylabel('WCSS')
plt.xticks(k)
plt.show()
```

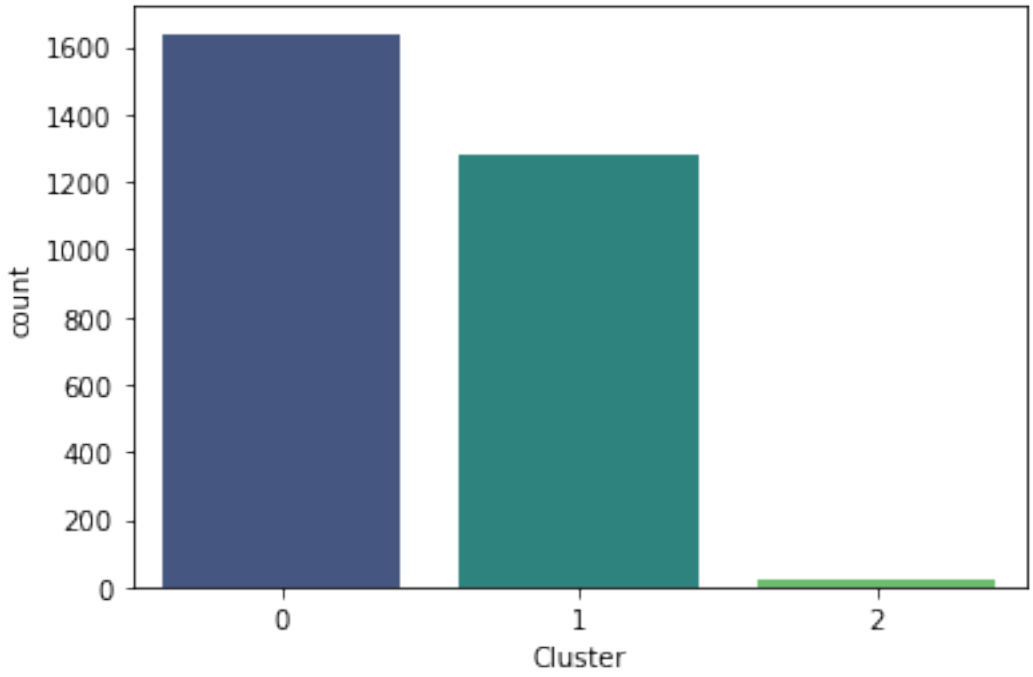


- optimum value for K = 3
- increase in the number of clusters, the WCSS value decreases
- select the value for K, the "elbow", on the basis of the rate of decrease, to indicate the model fits best at that point. In the graph, from cluster 1 to 2 to 3 in the above graph there is a huge drop in WCSS. After 3 the drop is minimal, thus we chose 3 to be the optimal value for K. Based on the Elbow Method, we can find the optimal number of clusters is 3. https://en.wikipedia.org/wiki/Elbow_method_(clustering)

[110]:
```
k_means = KMeans(n_clusters = 3, random_state = 100)
y_pred = k_means.fit_predict(pca_data)
pca_data['Cluster'] = y_pred
df['Cluster'] = y_pred
```

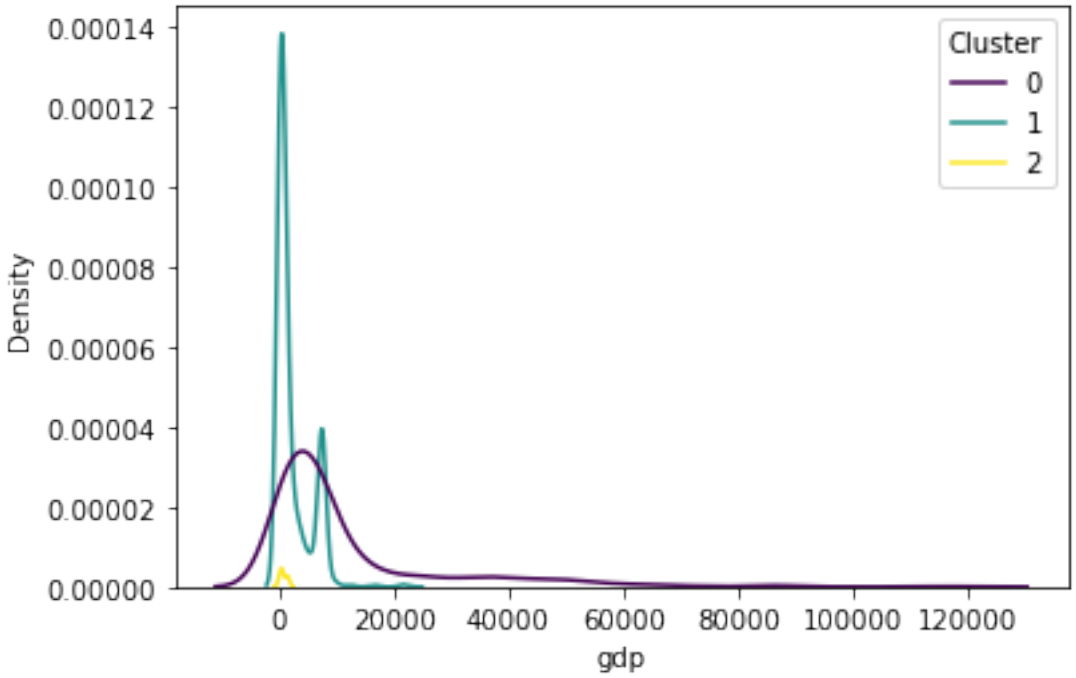
[118]:
```
sns.countplot(x=pca_data['Cluster'], palette = 'viridis')
```

[118]:
```
<AxesSubplot:xlabel='Cluster', ylabel='count'>
```



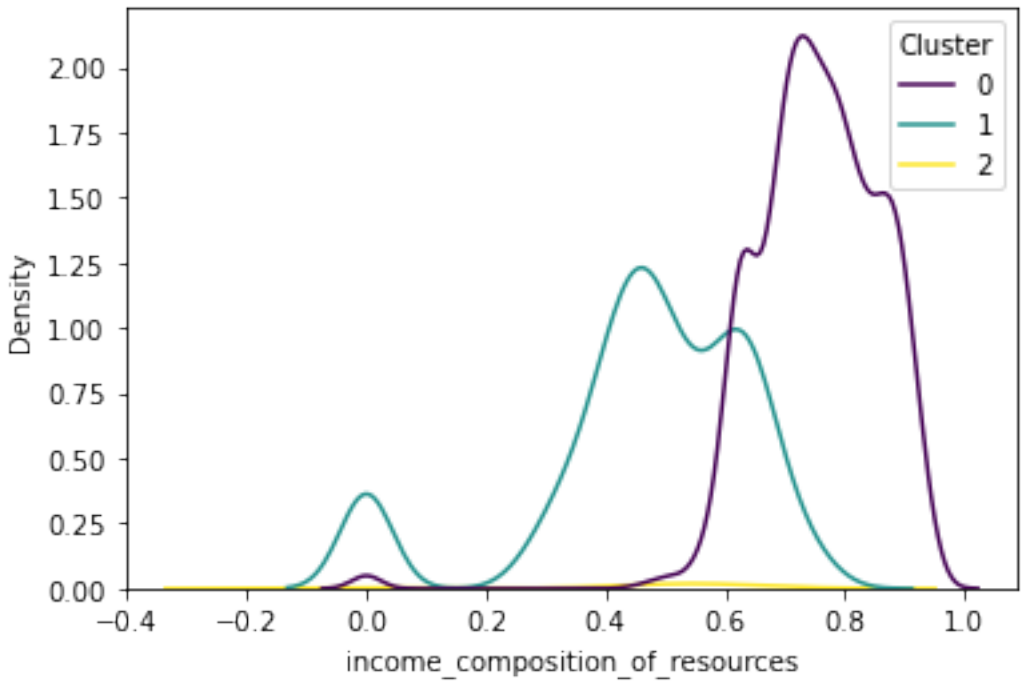
[122]:
```
#GDP
sns.kdeplot(data=df, x='gdp', hue='Cluster', palette = 'viridis')
```

[122]: <AxesSubplot:xlabel='gdp', ylabel='Density'>

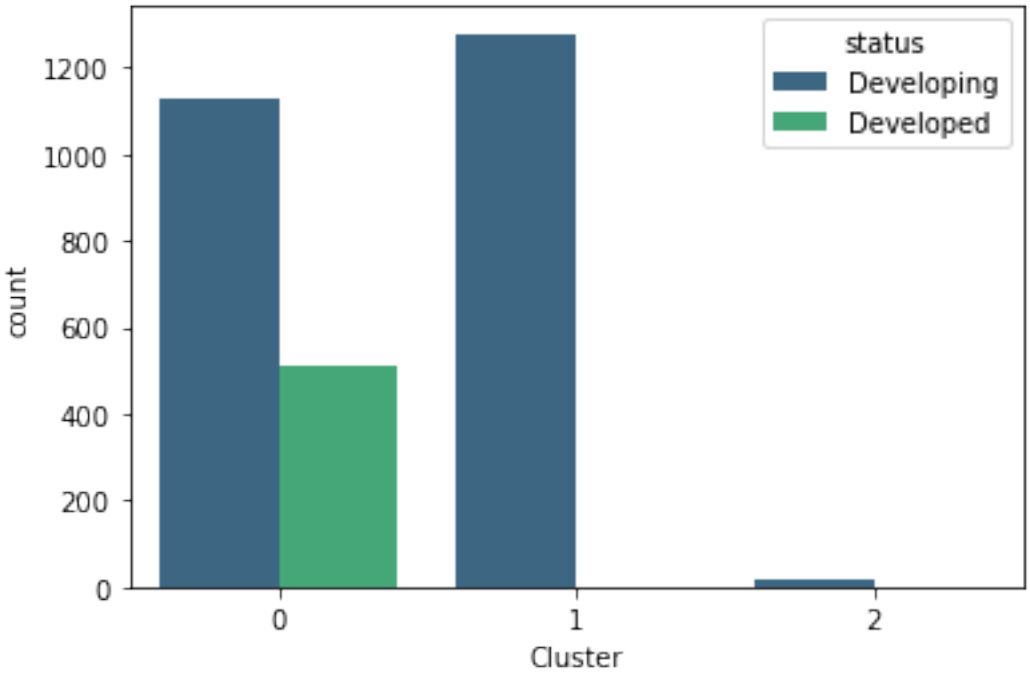


[123]:
```
#Income composition of resources
sns.kdeplot(data=df, x='income_composition_of_resources', hue='Cluster',␣
 ↪palette = 'viridis')
```

[123]: <AxesSubplot:xlabel='income_composition_of_resources', ylabel='Density'>



[116]:
```
#Status
profile = ['status']

for i in profile:
    plt.figure()
    sns.countplot(x='Cluster', data=df, hue=df[i],palette = 'viridis')
    plt.show()
```


status
Developing
Developed
1200
1000
800
600
400
200
0
count
0
1
2
Cluster