Final Project

March 7, 2023

1 Setup

[74]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math

import scipy as sp
import scipy.stats as stats
import seaborn as sns
import copy
# Set color map to have light blue background
sns.set()
import statsmodels.formula.api as smf
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
```

[96]:
```
'''data found at kaggle.com "Life Expectancy (WHO)"
https://www.kaggle.com/datasets/kumarajarshi/life-expectancy-who?
 ↪resource=download
'''
data = pd.read_csv('life_expectancy_data.csv')
```

2 Data Cleaning

[97]:
```
data.columns
```

[97]:
```
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')
```

[98]:
```
cols = ['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_to_19_years',
        'thinness_5_to_9_years', 'income_composition_of_resources', 'schooling']
data.columns = cols
data.head()
```

[98]:
```
       country  year      status  life_expectancy  adult_mortality  \
0  Afghanistan  2015  Developing             65.0            263.0
1  Afghanistan  2014  Developing             59.9            271.0
2  Afghanistan  2013  Developing             59.9            268.0
3  Afghanistan  2012  Developing             59.5            272.0
4  Afghanistan  2011  Developing             59.2            275.0

   infant_deaths  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  ...

   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

   thinness_1_to_19_years  thinness_5_to_9_years  \
0                    17.2                   17.3
1                    17.5                   17.5
2                    17.7                   17.7
3                    17.9                   18.0
4                    18.2                   18.2

   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

[5 rows x 22 columns]
```

[99]:

```
a = [np.nan, None, [], {}, 'NaN', 'Null','NULL','None','NA','?','-', '.','', '␣
↪', '   ']
for c in data.columns:
    string_null = np.array([x in a[2:] for x in data[c]])
    print(c, data[c].isnull().sum(), string_null.sum())
```

```
country 0 0
year 0 0
status 0 0
life_expectancy 10 0
adult_mortality 10 0
infant_deaths 0 0
alcohol 194 0
percentage_expenditure 0 0
hepatitis_b 553 0
measles 0 0
BMI 34 0
under_five_deaths 0 0
polio 19 0
total_expenditure 226 0
diphtheria 19 0
HIV_AIDS 0 0
GDP 448 0
population 652 0
thinness_1_to_19_years 34 0
thinness_5_to_9_years 34 0
income_composition_of_resources 167 0
schooling 163 0
```

[100]:

```
percentages = [i/1460 for i in data.isnull().sum()]
CCA = pd.DataFrame({'features': data.columns, 'percentage_missing':␣
↪percentages})
impute = []
throw = []
for i in np.arange(len(CCA)):
    if CCA['percentage_missing'][i] > 0.1:
        throw.append(CCA['features'][i])
    elif CCA['percentage_missing'][i] > 0 and CCA['percentage_missing'][i] <= 0.
↪05:
        impute.append(CCA['features'][i])
    else:
        continue


# Complete the codes below by uncommenting and changing the values of␣
↪features_to_impute and features_to_throw.
```

```
# Each should be a list of feature names (e.g. ['LotFrontage','Alley',...]). Do␣
↪not change the variable names.
# There are hidden tests which will grade above three questions.

features_to_impute = impute
features_to_throw = throw

print(len(features_to_impute), features_to_impute)
print(len(features_to_throw), features_to_throw)
```

```
7 ['life_expectancy', 'adult_mortality', 'BMI', 'polio', 'diphtheria',
'thinness_1_to_19_years', 'thinness_5_to_9_years']
7 ['alcohol', 'hepatitis_b', 'total_expenditure', 'GDP', 'population',
'income_composition_of_resources', 'schooling']
```

[101]:
```
data = data.drop(features_to_throw, 1)
```

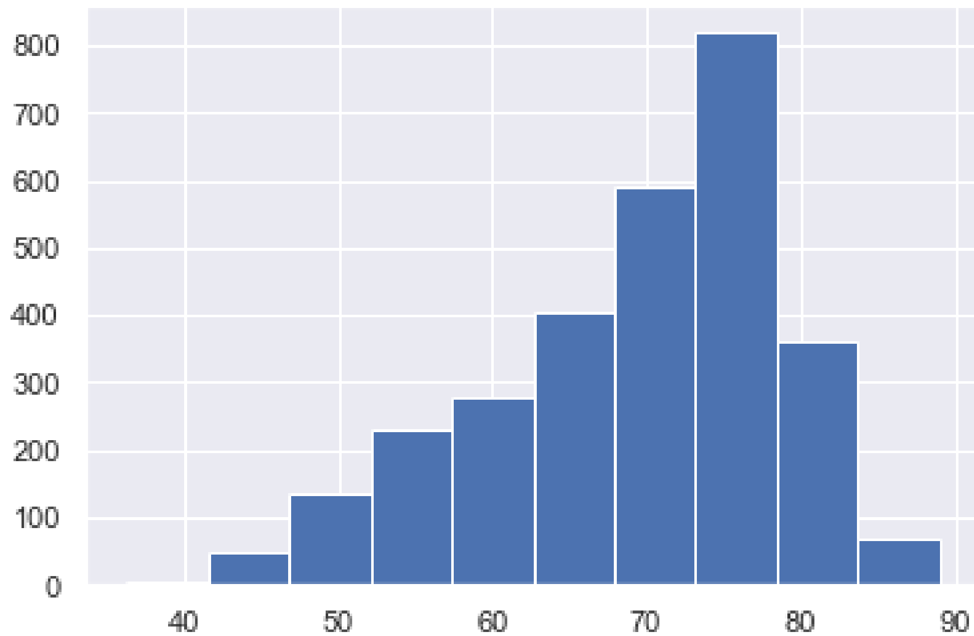
[102]:
```
temp_df = data
impute_dict = {}
for i in features_to_impute:
    if temp_df[i].dtype == float:
        impute_dict[i] = temp_df[i].median()
    else:
        impute_dict[i] = temp_df[i].mode().iloc[0]
temp_df = temp_df.fillna(value=impute_dict)
data = temp_df
data.head()
```

[102]:
```
       country  year      status  life_expectancy  adult_mortality  \
0  Afghanistan  2015  Developing             65.0            263.0
1  Afghanistan  2014  Developing             59.9            271.0
2  Afghanistan  2013  Developing             59.9            268.0
3  Afghanistan  2012  Developing             59.5            272.0
4  Afghanistan  2011  Developing             59.2            275.0

   infant_deaths  percentage_expenditure  measles   BMI  under_five_deaths  \
0             62               71.279624     1154  19.1                 83
1             64               73.523582      492  18.6                 86
2             66               73.219243      430  18.1                 89
3             69               78.184215     2787  17.6                 93
4             71                7.097109     3013  17.2                 97

   polio  diphtheria  HIV_AIDS  thinness_1_to_19_years  thinness_5_to_9_years
0    6.0        65.0       0.1                    17.2                   17.3
1   58.0        62.0       0.1                    17.5                   17.5
2   62.0        64.0       0.1                    17.7                   17.7
3   67.0        67.0       0.1                    17.9                   18.0
4   68.0        68.0       0.1                    18.2                   18.2
```

3 Exploratory Data Analysis

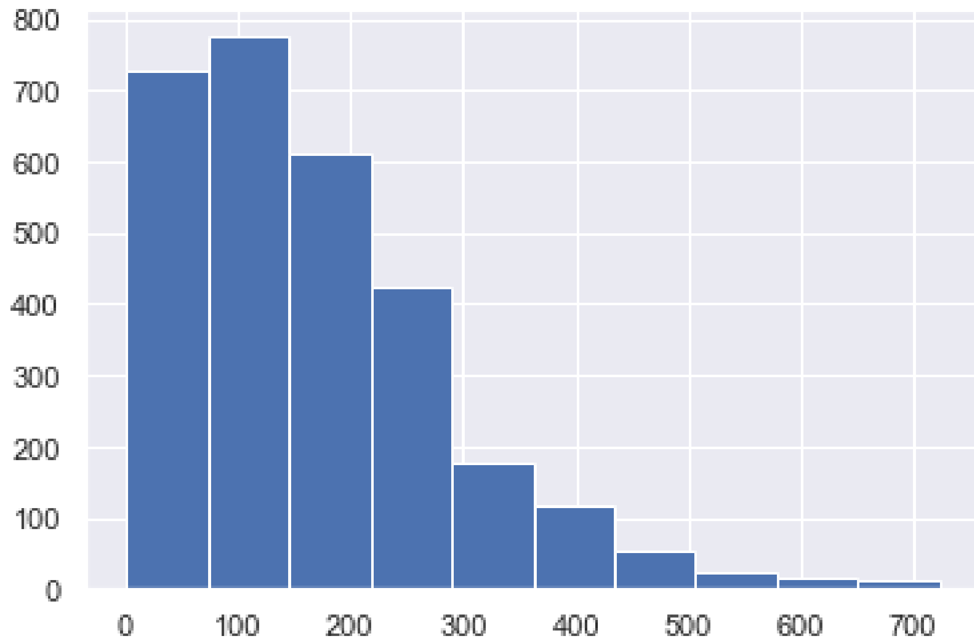
[103]:
```
plt.hist(data['life_expectancy'])
```

[103]:
```
(array([  4.,  50., 134., 229., 277., 405., 590., 819., 362.,  68.]),
 array([36.3 , 41.57, 46.84, 52.11, 57.38, 62.65, 67.92, 73.19, 78.46,
        83.73, 89.  ]),
 <a list of 10 Patch objects>)
```



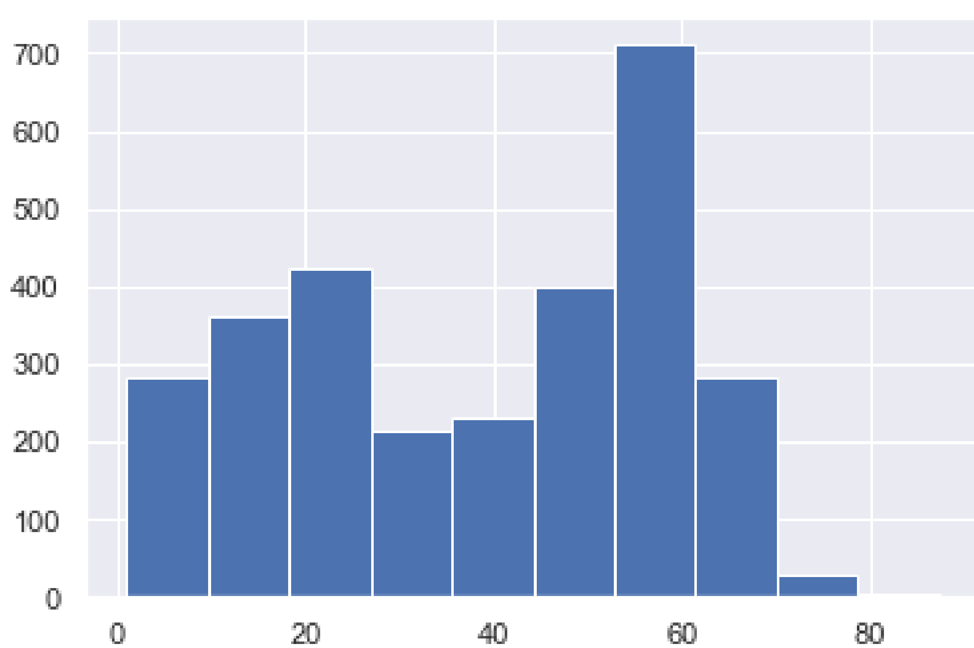
[104]:
```
plt.hist(data['adult_mortality'])
```

[104]:
```
(array([729., 775., 610., 423., 176., 117.,  54.,  24.,  17.,  13.]),
 array([  1. ,  73.2, 145.4, 217.6, 289.8, 362. , 434.2, 506.4, 578.6,
        650.8, 723. ]),
 <a list of 10 Patch objects>)
```



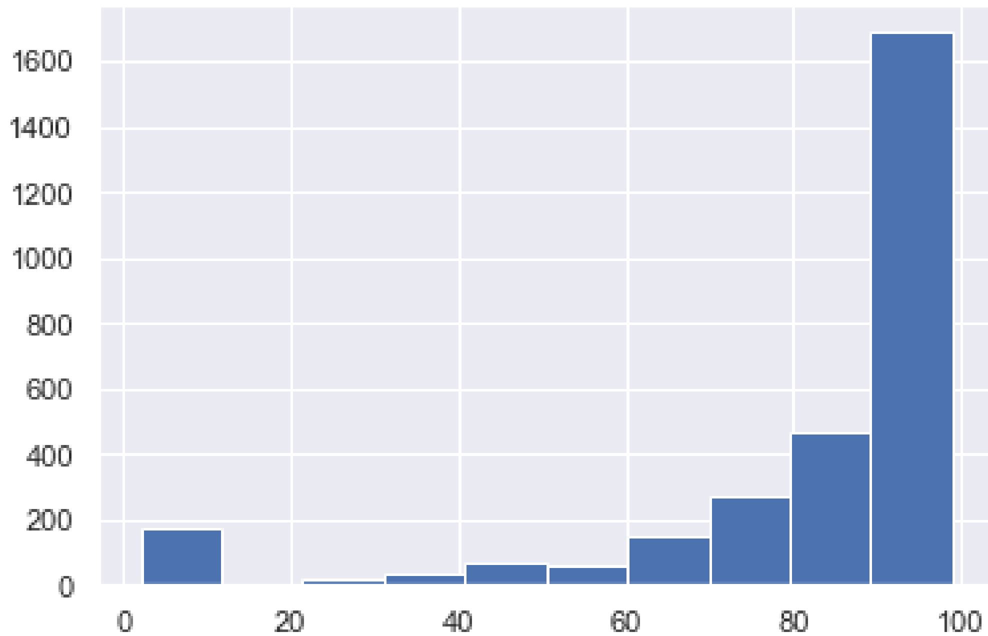
[105]:
```
plt.hist(data['BMI'])
```

[105]:
```
(array([283., 361., 423., 214., 230., 399., 711., 282.,  30.,   5.]),
 array([ 1.  ,  9.63, 18.26, 26.89, 35.52, 44.15, 52.78, 61.41, 70.04,
        78.67, 87.3 ]),
 <a list of 10 Patch objects>)
```



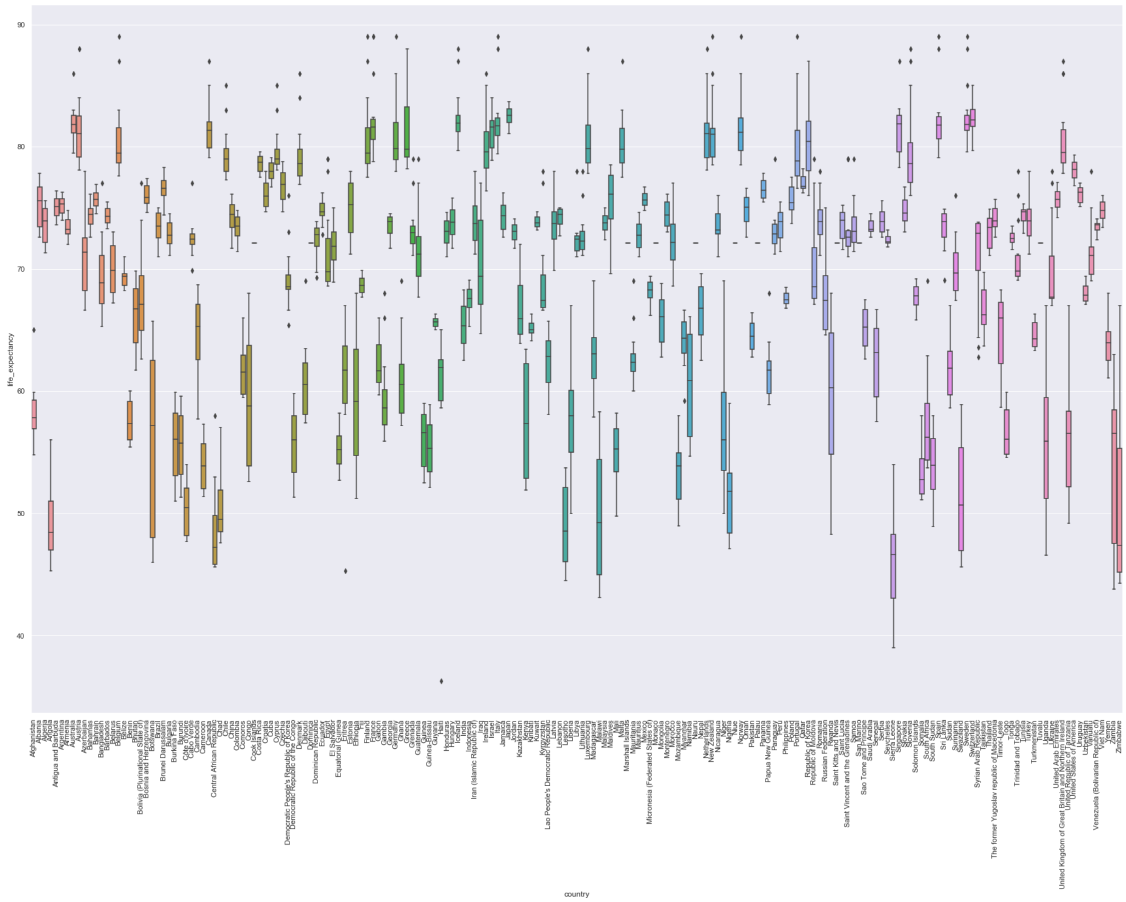
[106]:
```
plt.hist(data['diphtheria'])
```

[106]:
```
(array([ 170.,    3.,   22.,   35.,   68.,   59.,  150.,  272.,  470.,
        1689.]),
 array([ 2. , 11.7, 21.4, 31.1, 40.8, 50.5, 60.2, 69.9, 79.6, 89.3, 99. ]),
 <a list of 10 Patch objects>)
```



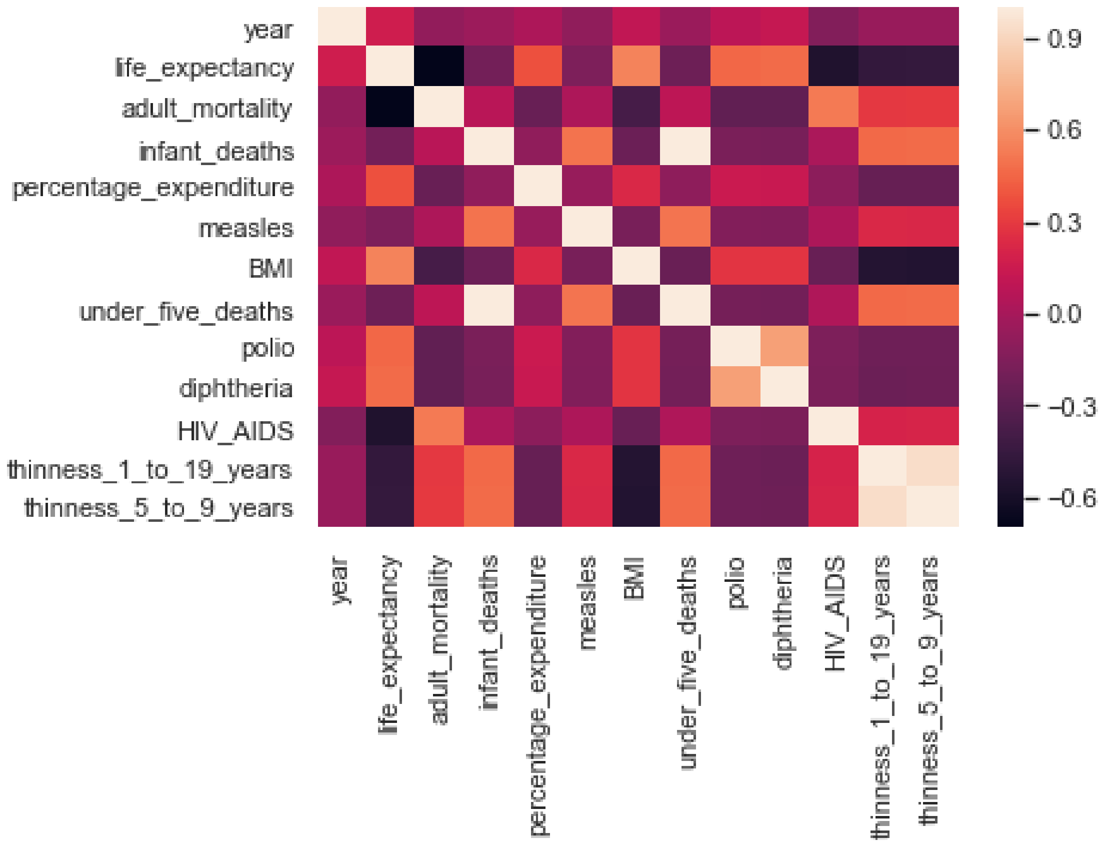
[119]:
```
plt.figure(figsize=(30,20))
plt.xticks(rotation=90)
sns.boxplot(y='life_expectancy',x='country',data=data)
```

[119]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fa8453a2a90>
```



[124]:
```
sns.heatmap(data.corr())
```

[124]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa84de86048>



4 Linear Regression

4.1 Simple

[108]:
```
from sklearn.model_selection import train_test_split
X = data
y = data['life_expectancy']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

[110]:
```
r_squared = {}
for i in X_train.columns:
    mod = smf.ols(formula='life_expectancy ~' + str(i), data=X_train)
    res = mod.fit()
    r_squared[i] = res.rsquared_adj

r_squared = {k: v for k, v in sorted(r_squared.items(), key=lambda item:␣
 ↪item[1])}
r_squared
```

[110]:
```
{'measles': 0.025318540986593252,
 'year': 0.026878528356840903,
 'infant_deaths': 0.036826989264662324,
 'under_five_deaths': 0.047374063265171906,
 'percentage_expenditure': 0.14561408092118355,
 'polio': 0.1957433957075454,
 'diphtheria': 0.2158979147783462,
 'thinness_5_to_9_years': 0.22300084543693088,
 'thinness_1_to_19_years': 0.22811648602720325,
 'status': 0.2345772013545615,
 'HIV_AIDS': 0.30458430629551136,
 'BMI': 0.3166738339020281,
 'adult_mortality': 0.4902125435114596,
 'country': 0.9199459436751365,
 'life_expectancy': 1.0}
```

4.2 Multiple

[126]:
```
y = data['life_expectancy']
X = data[['year', 'adult_mortality', 'infant_deaths', 'percentage_expenditure',␣
 ↪'measles', 'BMI',
          'under_five_deaths', 'diphtheria', 'HIV_AIDS',␣
 ↪'thinness_1_to_19_years', 'thinness_5_to_9_years']]
X = sm.add_constant(X)
mod = sm.OLS(y, X)
res = mod.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        life_expectancy   R-squared:                       0.739
Model:                            OLS   Adj. R-squared:                  0.738
Method:                 Least Squares   F-statistic:                     754.4
Date:                Mon, 06 Mar 2023   Prob (F-statistic):               0.00
Time:                        21:19:52   Log-Likelihood:                -8810.4
No. Observations:                2938   AIC:                         1.764e+04
Df Residuals:                    2926   BIC:                         1.772e+04
Df Model:                          11
Covariance Type:            nonrobust
================================================================================
==========
                             coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----------
const                   -113.8296     39.814     -2.859      0.004    -191.896
-35.763
```

```
year                          0.0893      0.020      4.495      0.000       0.050
0.128
adult_mortality              -0.0267      0.001    -28.905      0.000      -0.028
-0.025
infant_deaths                 0.1290      0.010     13.218      0.000       0.110
0.148
percentage_expenditure        0.0008   4.77e-05     16.829      0.000       0.001
0.001
measles                    -2.01e-05   9.18e-06     -2.190      0.029   -3.81e-05
-2.11e-06
BMI                           0.0886      0.006     15.588      0.000       0.077
0.100
under_five_deaths            -0.0953      0.007    -13.230      0.000      -0.109
-0.081
diphtheria                    0.0780      0.004     18.675      0.000       0.070
0.086
HIV_AIDS                     -0.4288      0.021    -20.384      0.000      -0.470
-0.388
thinness_1_to_19_years       -0.2466      0.060     -4.112      0.000      -0.364
-0.129
thinness_5_to_9_years        -0.0105      0.059     -0.177      0.859      -0.127
0.106
==============================================================================
Omnibus:                      152.745   Durbin-Watson:                   0.825
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              306.023
Skew:                          -0.364   Prob(JB):                     3.53e-67
Kurtosis:                       4.404   Cond. No.                     5.20e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 5.2e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[128]:

```python
y = data['life_expectancy']
X = data[['adult_mortality','thinness_1_to_19_years', 'thinness_5_to_9_years']]
X = sm.add_constant(X)
mod = sm.OLS(y, X)
res = mod.fit()
print(res.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:        life_expectancy   R-squared:                       0.561
Model:                            OLS   Adj. R-squared:                  0.560
Method:                 Least Squares   F-statistic:                     1248.
```

```
Date:                  Mon, 06 Mar 2023   Prob (F-statistic):            0.00
Time:                          23:05:39   Log-Likelihood:             -9577.1
No. Observations:                  2938   AIC:                      1.916e+04
Df Residuals:                      2934   BIC:                      1.919e+04
Df Model:                             3
Covariance Type:              nonrobust
================================================================================
==========
                          coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
----------
const                  79.9627      0.212    377.732      0.000      79.548
80.378
adult_mortality        -0.0467      0.001    -47.457      0.000      -0.049
-0.045
thinness_1_to_19_years -0.4735      0.077     -6.141      0.000      -0.625
-0.322
thinness_5_to_9_years  -0.1546      0.076     -2.042      0.041      -0.303
-0.006
==============================================================================
Omnibus:                       1010.049   Durbin-Watson:                 0.732
Prob(Omnibus):                    0.000   Jarque-Bera (JB):           4020.868
Skew:                            -1.655   Prob(JB):                       0.00
Kurtosis:                         7.679   Cond. No.                       376.
==============================================================================

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

4.3 Polynomial

[127]:
```python
data['adult_mortality_norm'] = data['adult_mortality']/data['adult_mortality'].
 ↪mean()
# your code here
X = data
y = data['life_expectancy']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

running_string = 'life_expectancy ~ adult_mortality_norm'
for i in np.arange(2,21):
    running_string += ' + np.power(adult_mortality_norm,'+str(i)+')'
    mod = smf.ols(formula=running_string, data=X_train)
    res = mod.fit()
    print(str(i) + ' : ' + str(res.rsquared))
```

```
2 : 0.49193716431767087
3 : 0.5692938325517775
4 : 0.5946281196722973
5 : 0.5946621909434657
6 : 0.6011052555387206
7 : 0.611308773853815
8 : 0.6280577613186283
9 : 0.6472735241027582
10 : 0.6546820290399624
11 : 0.6547034949639421
12 : 0.6605546147782162
13 : 0.6846285839950164
14 : 0.7155454313295463
15 : 0.7359601457143119
16 : 0.7463385611974666
17 : 0.7367887909220315
18 : 0.7164770381591825
19 : 0.6664736603389467
20 : 0.6695909554613906
```

5 Conclusion

This dataset has a variety of features, including but not limited to, country, disease, adult and infant mortality, and BMI. I chose to use a combination of these features to predict life expectancy using linear regression models.

Starting with data cleaning, I identified columns that had above a 10% missing value percentage, and imputed those that were missing below 10%. I upped the threshold from 5% to 10%, as more than half of the columns had more than 5% missing values. I also renamed the columns, as they were incosistent and often had spaces before and after the column names.

In terms of exploratory data analysis, I chose to explore the distribution of a few of the continuous variables, and also used a boxplot for some insight into the distribution of the life expectancy of each country. Finally, I ended with a correlation matrix to see what features may be the strongest predictors for life expectancy.

In the simple model, the number one predictor of life expectancy was country with an adjusted r-squared value of 0.9199. For the multiple linear regression model, I tried two different models – one using all of the continuous-variable columns remaining after data cleaning, and one using the three seemingly most strongly, although negatively, correlated features. Finally, I used a polynomial model with the best scoring continuous variable (adult_mortality, normalized), and found that it peaked at the 16th degree.

[ ]:
```

```