GDP and life satisfaction

June 6, 2021

[88]:
```
# Here are imported the libraries/modules that are used below for the analysis.

#%matplotlib notebook
%matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
import scipy as sp
import pandas as pd
import sklearn as sk
from sklearn import neighbors
from sklearn.metrics import mean_squared_error
import seaborn as sns
```

[89]:
```
# Here I use my local file path on reading the .csv files.
# The reader must use the appropriate path where files are located in their␣
↪computers.

# I select as header the third row of the file gdp per capita (n=2). The␣
↪delimiter is ","
GDP=pd.read_csv("/Users/damianejlli/Downloads/gdp per capita.csv",␣
↪delimiter=",", header=2)

# There is no need to specify the header for the "better life index.csv" file.
LS=pd.read_csv("/Users/damianejlli/Downloads/better life index.csv")
```

[90]:
```
#I display some of the content of the GDP dataframe.

GDP.head()
```

[90]:
```
  Country Name Country Code                Indicator Name  Indicator Code  \
0        Aruba          ABW  GDP per capita (current US$)  NY.GDP.PCAP.CD
1  Afghanistan          AFG  GDP per capita (current US$)  NY.GDP.PCAP.CD
2       Angola          AGO  GDP per capita (current US$)  NY.GDP.PCAP.CD
3      Albania          ALB  GDP per capita (current US$)  NY.GDP.PCAP.CD
4      Andorra          AND  GDP per capita (current US$)  NY.GDP.PCAP.CD

        1960       1961       1962       1963       1964        1965  …  \
```

```
0         NaN        NaN        NaN        NaN        NaN         NaN  …
1   59.773194  59.860874  58.458015  78.706388  82.095231  101.108305  …
2         NaN        NaN        NaN        NaN        NaN         NaN  …
3         NaN        NaN        NaN        NaN        NaN         NaN  …
4         NaN        NaN        NaN        NaN        NaN         NaN  …

           2012          2013          2014          2015          2016  \
0  24713.698045  26189.435509  26647.938101  27980.880695  28281.350482
1    641.871479    637.165523    613.856689    578.466353    509.218661
2   5100.095808   5254.882338   5408.410496   4166.979684   3506.072885
3   4247.629984   4413.060861   4578.631994   3952.801215   4124.055726
4  38686.461264  39538.766722  41303.929371  35762.523074  37474.665406

           2017          2018          2019  2020  Unnamed: 65
0  29007.693003           NaN           NaN   NaN          NaN
1    519.884773    493.750418    507.103432   NaN          NaN
2   4095.812942   3289.646664   2790.726615   NaN          NaN
3   4531.020806   5284.380184   5353.244856   NaN          NaN
4  38962.880354  41793.055258  40886.391165   NaN          NaN

[5 rows x 66 columns]
```

[91]:
```
# I select the columns "Country Name" and year "2015" for the analysis in the
↪GDP dataframe.

GPD1=GDP.loc[:,["Country Name", '2015']]
```

[92]:
```
# I display the GDP1 dataframe content.

GPD1
```

[92]:
```
     Country Name          2015
0           Aruba  27980.880695
1     Afghanistan    578.466353
2          Angola   4166.979684
3         Albania   3952.801215
4         Andorra  35762.523074
..            …             …
259        Kosovo   3603.025501
260   Yemen, Rep.   1602.037841
261  South Africa   5734.633629
262        Zambia   1337.795586
263      Zimbabwe   1445.071062

[264 rows x 2 columns]
```

[93]:
```python
# I set as index the "Country Name" column and rename the column "2015" to "GPD␣
↪per capita 2015 (USD)"
# and I set the dataframe in alphabetic order

GDP2=GPD1.set_index("Country Name").rename(columns={"2015": "GDP per capita␣
↪2015 (USD)"}).sort_index()
```

[94]:
```python
# I show the first ten rows of the GDP2 dataframe as a matter of example
# print(GDP2.to_string())

GDP2.head(10)
```

[94]:
```
                     GDP per capita 2015 (USD)
Country Name
Afghanistan                         578.466353
Albania                            3952.801215
Algeria                            4187.509727
American Samoa                    11843.331183
Andorra                           35762.523074
Angola                             4166.979684
Antigua and Barbuda               14286.093160
Arab World                         6400.360350
Argentina                         13789.060425
Armenia                            3607.296697
```

[95]:
```python
# I show the first five rows of the LS dataframe as a matter of example.

LS.head()
```

[95]:
```
  LOCATION         Country INDICATOR                 Indicator MEASURE  \
0      AUS       Australia   JE_LMIS  Labour market insecurity       L
1      AUT         Austria   JE_LMIS  Labour market insecurity       L
2      BEL         Belgium   JE_LMIS  Labour market insecurity       L
3      CAN          Canada   JE_LMIS  Labour market insecurity       L
4      CZE  Czech Republic   JE_LMIS  Labour market insecurity       L

  Measure INEQUALITY Inequality Unit Code        Unit  PowerCode Code  \
0   Value        TOT      Total        PC  Percentage               0
1   Value        TOT      Total        PC  Percentage               0
2   Value        TOT      Total        PC  Percentage               0
3   Value        TOT      Total        PC  Percentage               0
4   Value        TOT      Total        PC  Percentage               0

  PowerCode  Reference Period Code  Reference Period  Value  Flag Codes  Flags
0     Units                    NaN               NaN    5.4         NaN    NaN
1     Units                    NaN               NaN    3.5         NaN    NaN
2     Units                    NaN               NaN    3.7         NaN    NaN
```

```
3     Units                      NaN               NaN     6.0            NaN     NaN
4     Units                      NaN               NaN     3.1            NaN     NaN
```

[96]:
```
# I show the shape of the LS dataframe. It has 2369 rows and 17 columns.

LS.shape
```

[96]:
```
(2369, 17)
```

[97]:
```
# I use a conditional to choose all those rows with values "Life satisfaction"␣
↪in the column "Indicator"
# and all those equal to "TOT" in the "INEQUALITY" column in the LS dataframe.
# "TOT" is the total value of life satisfaction for men and women in a given␣
↪country.

LS1=LS[(LS["Indicator"]=="Life satisfaction") & (LS["INEQUALITY"]=="TOT")]
```

[98]:
```
# I show the first 10 entries of the LS1 dataframe as a matter of exmple.

LS1.head(10)
```

[98]:
```
     LOCATION         Country INDICATOR         Indicator MEASURE Measure  \
1813      AUS       Australia   SW_LIFS Life satisfaction       L   Value
1814      AUT         Austria   SW_LIFS Life satisfaction       L   Value
1815      BEL         Belgium   SW_LIFS Life satisfaction       L   Value
1816      CAN          Canada   SW_LIFS Life satisfaction       L   Value
1817      CZE  Czech Republic   SW_LIFS Life satisfaction       L   Value
1818      DNK         Denmark   SW_LIFS Life satisfaction       L   Value
1819      FIN         Finland   SW_LIFS Life satisfaction       L   Value
1820      FRA          France   SW_LIFS Life satisfaction       L   Value
1821      DEU         Germany   SW_LIFS Life satisfaction       L   Value
1822      GRC          Greece   SW_LIFS Life satisfaction       L   Value

     INEQUALITY Inequality Unit Code           Unit  PowerCode Code PowerCode  \
1813        TOT      Total   AVSCORE  Average score               0     Units
1814        TOT      Total   AVSCORE  Average score               0     Units
1815        TOT      Total   AVSCORE  Average score               0     Units
1816        TOT      Total   AVSCORE  Average score               0     Units
1817        TOT      Total   AVSCORE  Average score               0     Units
1818        TOT      Total   AVSCORE  Average score               0     Units
1819        TOT      Total   AVSCORE  Average score               0     Units
1820        TOT      Total   AVSCORE  Average score               0     Units
1821        TOT      Total   AVSCORE  Average score               0     Units
1822        TOT      Total   AVSCORE  Average score               0     Units

      Reference Period Code  Reference Period  Value  Flag Codes  Flags
1813                    NaN               NaN    7.3         NaN    NaN
```

```
1814                    NaN              NaN    7.1         NaN    NaN
1815                    NaN              NaN    6.9         NaN    NaN
1816                    NaN              NaN    7.4         NaN    NaN
1817                    NaN              NaN    6.7         NaN    NaN
1818                    NaN              NaN    7.6         NaN    NaN
1819                    NaN              NaN    7.6         NaN    NaN
1820                    NaN              NaN    6.5         NaN    NaN
1821                    NaN              NaN    7.0         NaN    NaN
1822                    NaN              NaN    5.4         NaN    NaN
```

[99]:
```
# First, in the LS1 dataframe, I rename the columns "Country" and "Value"␣
↪respectively to "Country Name" and "Life Satisfaction Value".
# Second, I set as index of the new dataframe the "Country Name" and after I␣
↪select all rows in the "Indicator" column
# with entries equal to "Life Satisfaction Value". After the results are sorted␣
↪alphabetically.

LS2=LS1.rename(columns={"Country" : "Country Name", "Value": "Life Satisfaction␣
↪Value"}).set_index("Country Name").loc[:, ["Life Satisfaction Value"]].
↪sort_index()
```

[100]:
```
# I show the first 10 entries of the LS2 dataframe as a matter of exmple.

LS2.head(10)
```

[100]:
```
                Life Satisfaction Value
Country Name
Australia                           7.3
Austria                             7.1
Belgium                             6.9
Brazil                              6.4
Canada                              7.4
Chile                               6.5
Colombia                            6.3
Czech Republic                      6.7
Denmark                             7.6
Estonia                             5.7
```

[101]:
```
# I remove the entry "OECD-Total" country index from the LS2 dataframe because␣
↪it is unneccessary for the analysis.

LS3=LS2[LS2.index != "OECD - Total"]
```

[102]:
```
# I show the first 10 entries of the LS3 dataframe as a matter of exmple.

LS3.head(10)
```

[102]:

Country Name	Life Satisfaction Value
Australia	7.3
Austria	7.1
Belgium	6.9
Brazil	6.4
Canada	7.4
Chile	6.5
Colombia	6.3
Czech Republic	6.7
Denmark	7.6
Estonia	5.7

[103]:

```
# I join the LS3 dataframe with the GPD2 dataframe in order to form the final␣
↪dataframe, df.

df=LS3.join(GDP2)
```

[104]:

```
# I display the entries in the joint dataframe, df.

df
```

[104]:

Country Name	Life Satisfaction Value	GDP per capita 2015 (USD)
Australia	7.3	56755.721712
Austria	7.1	44178.047378
Belgium	6.9	40991.808138
Brazil	6.4	8814.000987
Canada	7.4	43585.511982
Chile	6.5	13574.171831
Colombia	6.3	6175.876030
Czech Republic	6.7	17829.698322
Denmark	7.6	53254.856370
Estonia	5.7	17522.230186
Finland	7.6	42784.698362
France	6.5	36638.184929
Germany	7.0	41086.729674
Greece	5.4	18167.773727
Hungary	5.6	12706.891215
Iceland	7.5	52564.429179
Ireland	7.0	61995.422803
Israel	7.2	35776.795162
Italy	6.0	30230.226302
Japan	5.9	34524.469861
Korea	5.9	NaN
Latvia	5.9	13774.605274
Lithuania	5.9	14258.229335

Luxembourg	6.9	101376.496574
Mexico	6.5	9616.645006
Netherlands	7.4	45175.231893
New Zealand	7.3	38615.995185
Norway	7.6	74355.515858
Poland	6.1	12578.495473
Portugal	5.4	19242.366471
Russia	5.8	NaN
Slovak Republic	6.2	16310.988409
Slovenia	5.9	20881.766930
South Africa	4.7	5734.633629
Spain	6.3	25732.018365
Sweden	7.3	51545.483610
Switzerland	7.5	82081.597162
Turkey	5.5	11006.249736
United Kingdom	6.8	44974.831877
United States	6.9	56839.381774

[105]:
```
# I remove the NaN values from the "df" dataframe to form the final dataframe␣
↪for the analysis, "df1".

df1=df.dropna()
```

[106]:
```
# I display the df1 dataframe.

df1
```

[106]:

	Life Satisfaction Value	GDP per capita 2015 (USD)
Country Name		
Australia	7.3	56755.721712
Austria	7.1	44178.047378
Belgium	6.9	40991.808138
Brazil	6.4	8814.000987
Canada	7.4	43585.511982
Chile	6.5	13574.171831
Colombia	6.3	6175.876030
Czech Republic	6.7	17829.698322
Denmark	7.6	53254.856370
Estonia	5.7	17522.230186
Finland	7.6	42784.698362
France	6.5	36638.184929
Germany	7.0	41086.729674
Greece	5.4	18167.773727
Hungary	5.6	12706.891215
Iceland	7.5	52564.429179
Ireland	7.0	61995.422803
Israel	7.2	35776.795162

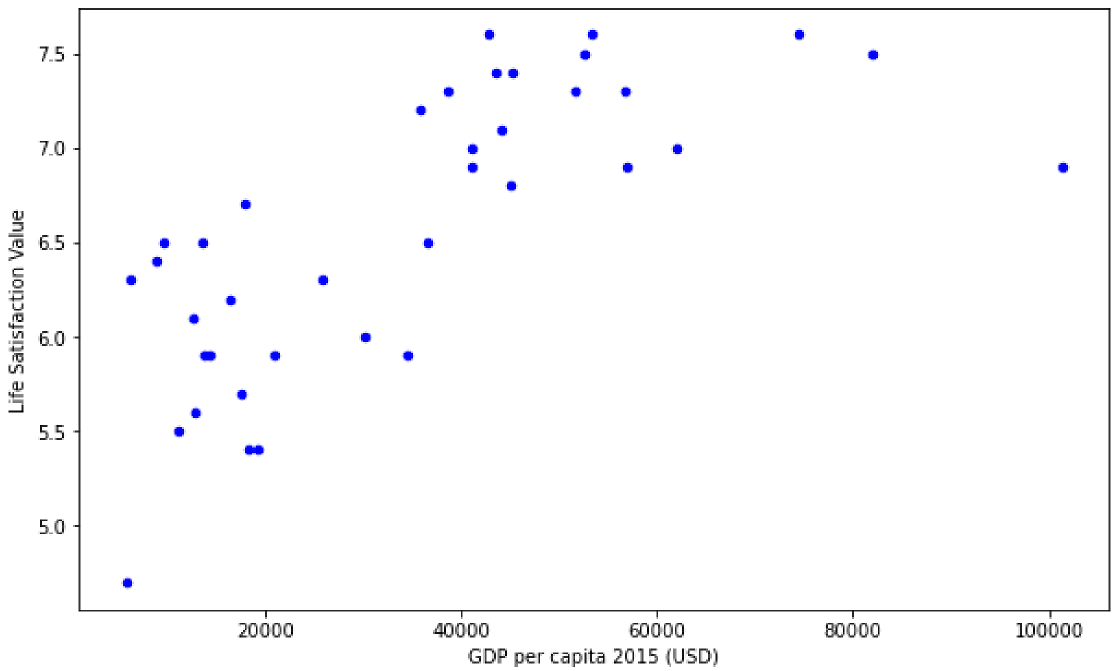
```
Italy                         6.0         30230.226302
Japan                         5.9         34524.469861
Latvia                        5.9         13774.605274
Lithuania                     5.9         14258.229335
Luxembourg                    6.9        101376.496574
Mexico                        6.5          9616.645006
Netherlands                   7.4         45175.231893
New Zealand                   7.3         38615.995185
Norway                        7.6         74355.515858
Poland                        6.1         12578.495473
Portugal                      5.4         19242.366471
Slovak Republic               6.2         16310.988409
Slovenia                      5.9         20881.766930
South Africa                  4.7          5734.633629
Spain                         6.3         25732.018365
Sweden                        7.3         51545.483610
Switzerland                   7.5         82081.597162
Turkey                        5.5         11006.249736
United Kingdom                6.8         44974.831877
United States                 6.9         56839.381774
```

[107]:
```
# I calculate the shape of the df1 dataframe. The dataframe has 38 rows and 2␣
↪columns.

df1.shape
```

[107]:
```
(38, 2)
```

[108]:
```
# I create a scatter plot for the data in the df1 dataframe.

df1.plot(kind="scatter", x="GDP per capita 2015 (USD)", y="Life Satisfaction␣
↪Value", color="b", figsize=(10,6))
```

[108]:
```
<AxesSubplot:xlabel='GDP per capita 2015 (USD)', ylabel='Life Satisfaction
Value'>
```



[109]:
```
# I calculate the Pearson correlation coeffeicient r for the data in the df1␣
↪dataframe
# and display the correlation dataframe.

df1.corr()
```

[109]:

	Life Satisfaction Value	GDP per capita 2015 (USD)
Life Satisfaction Value	1.000000	0.720287
GDP per capita 2015 (USD)	0.720287	1.000000

[110]:
```
# I extract all values of the "GPD per capita 2015 (USD)" and "Life␣
↪Satisfaction Value" columns and
# form new (38x1) column arrays "a" and "b".

a=df1.loc[:, ["GDP per capita 2015 (USD)"]].values
b=df1.loc[:, ["Life Satisfaction Value"]].values
```

[111]:
```
# I reshape the original (38x1) column arrary "a" to a (1x38) row array "X".

X=a.reshape(38)
```

[112]:
```
# I display the "X" array.

X
```

[112]:
```
array([ 56755.72171242,  44178.04737774,  40991.80813814,   8814.00098681,
        43585.51198178,  13574.17183072,   6175.8760297 ,  17829.69832237,
        53254.85637009,  17522.23018625,  42784.69836164,  36638.18492916,
        41086.72967373,  18167.77372717,  12706.89121489,  52564.42917946,
        61995.42280258,  35776.79516181,  30230.22630213,  34524.46986093,
        13774.60527391,  14258.22933451, 101376.49657434,   9616.64500569,
        45175.23189338,  38615.99518491,  74355.51585756,  12578.49547344,
        19242.3664711 ,  16310.988409  ,  20881.76692993,   5734.63362915,
        25732.01836475,  51545.48360953,  82081.59716162,  11006.2497364 ,
        44974.83187718,  56839.38177423])
```

[113]:
```
# I reshape the original (38x1) column "b" array to a (1x38) row array "y".

y=b.reshape(38)
```

[114]:
```
# I display the "y" array.
y
```

[114]:
```
array([7.3, 7.1, 6.9, 6.4, 7.4, 6.5, 6.3, 6.7, 7.6, 5.7, 7.6, 6.5, 7. ,
       5.4, 5.6, 7.5, 7. , 7.2, 6. , 5.9, 5.9, 5.9, 6.9, 6.5, 7.4, 7.3,
       7.6, 6.1, 5.4, 6.2, 5.9, 4.7, 6.3, 7.3, 7.5, 5.5, 6.8, 6.9])
```

[115]:
```
# First, I assume a simple linear regression model for the data in "X" and "y"␣
↪arrays
# and calculate the slope, intercept etc., of the linear regression method.
# Here I use the "stats" module of "Scipy" library and its linear regression␣
↪built in method.

result = sp.stats.linregress(X, y)
```

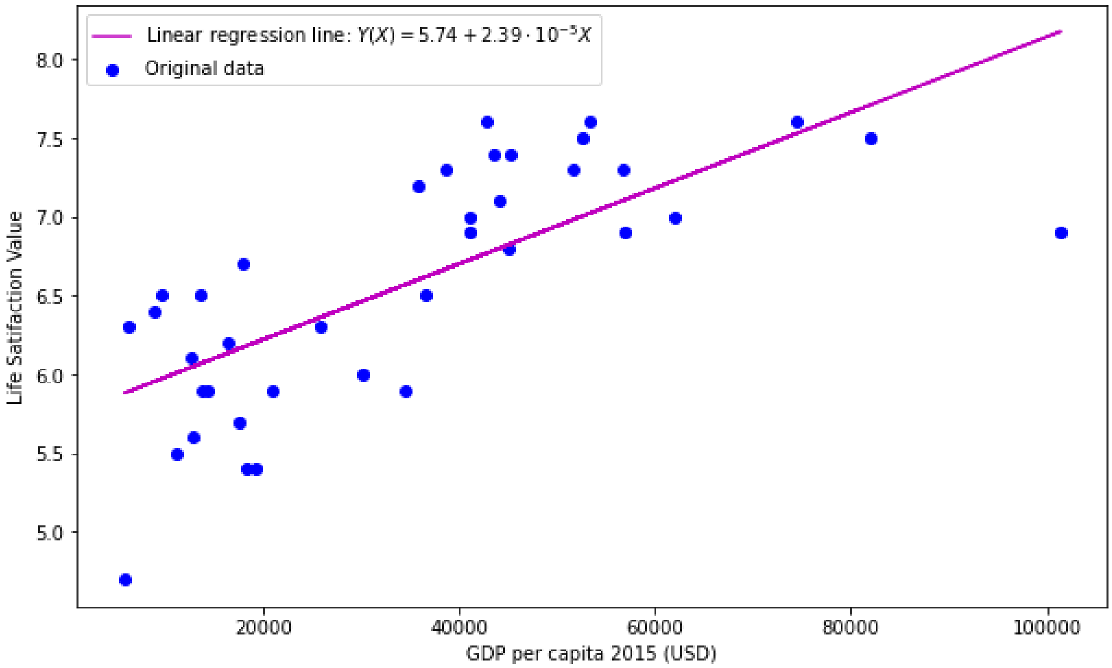
[116]:
```
# I print the results of the simple linear regression method.

print(result)
```

```
LinregressResult(slope=2.3996299825729615e-05, intercept=5.7417543537553195,
rvalue=0.7202871953226535, pvalue=3.426556470065171e-07,
stderr=3.851624914535905e-06, intercept_stderr=0.15853194959552194)
```

[117]:
```
# I create a figure with a single subplot where the original data of the df1␣
↪dataframe
# and the linear regression line Y(X) are shown.

fig, ax=plt.subplots(figsize=(10, 6))
ax.scatter(X, y, color='b', label="Original data")
ax.plot(X, result.intercept + (result.slope)*X, color="m", label="Linear␣
↪regression line: $Y(X)=5.74+2.39\cdot 10^{-5} X$")
ax.set_xlabel("GDP per capita 2015 (USD)")
```

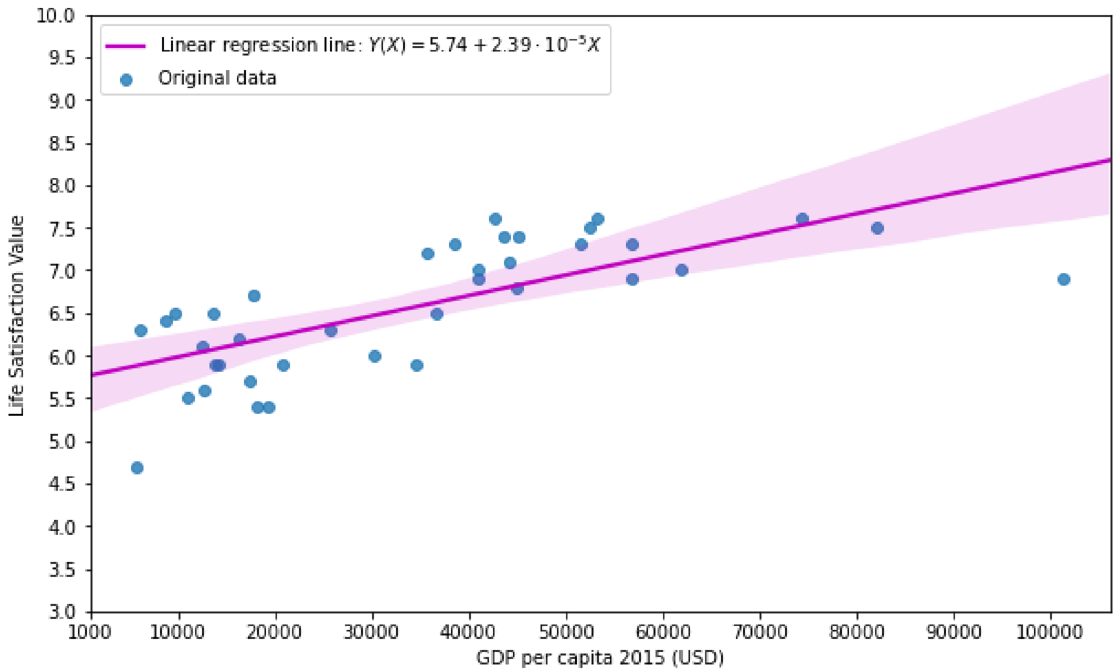
```
ax.set_ylabel("Life Satifaction Value")
plt.legend()
```

[117]: <matplotlib.legend.Legend at 0x7faf477c7eb0>




```
[118]: # I show the linear regression line together with the 95% confidence interval␣
↪for the regression parameters
# and the original data by using seaborn module.

fig, ax = plt.subplots(figsize=(10, 6))
sns.regplot(x="GDP per capita 2015 (USD)", y="Life Satisfaction Value",␣
↪data=df1, ci=95, order=1,line_kws={'label': 'Linear regression line: $Y(X)=5.
↪74+2.39\cdot 10^{-5} X$', 'color': 'm'}, seed=1,truncate=False,␣
↪label="Original data")
ax.set_xticks([1000, 10000, 20000, 30000, 40000, 50000, 60000, 70000, 80000,␣
↪90000, 100000])
ax.set_yticks(np.arange(3.0, 10.5, 0.5))
ax.legend(loc="upper left")
```

[118]: <matplotlib.legend.Legend at 0x7faf4819fc40>



[119]:
```
# I calculate the t-score in order to estimate the Confidence Intervals (CIs)
# of the linear regression coefficients "beta_0" and "beta_1" at significance
# level of alpha=0.05 and Confidence Level (CL) of 95%. The number of degrees␣
↪of freedom for the data is n=38.

n=38
alpha=0.05
t_score = sp.stats.t.ppf(1-alpha/2, n-2)
print("Model t_score: ", t_score)
```

```
Model t_score:  2.0280940009804502
```

[120]:
```
# Second, I use the KNN regression method to find a relationship between the␣
↪data for K=5 (default value).

model=sk.neighbors.KNeighborsRegressor(n_neighbors=5)
```

[121]:
```
# I use the fit() function to fit the data of the KNN method
# and reshape the X and y 1D arrays to form 2D arrays to use for the KNN method.

model.fit(X.reshape(-1, 1),y.reshape(-1, 1))
```

[121]:
```
KNeighborsRegressor()
```

[122]:
```
# I calculate the predicted values of the KNN method for
# the GDP data "X" not present in the df1 dataframe for the countries of␣
↪Albania, United Arab Emirates and Armenia.

X_new=[[3952.801215],[38663.383807],[3607.296697]]
```

[123]:
```
# I Print the predicted values of "Life Satisfaction Value" respectively
# for Albania, United Arab Emirates and Armenia.

print(model.predict(X_new))
```

```
[[5.88]
 [6.98]
 [5.88]]
```

[124]:
```
# I print the value of the generalized correlation coefficient R^2 for the KNN␣
↪model for K=5.

print("Model R^2 value: ", model.score(X.reshape(-1, 1),y.reshape(-1, 1),␣
↪sample_weight=None))
```

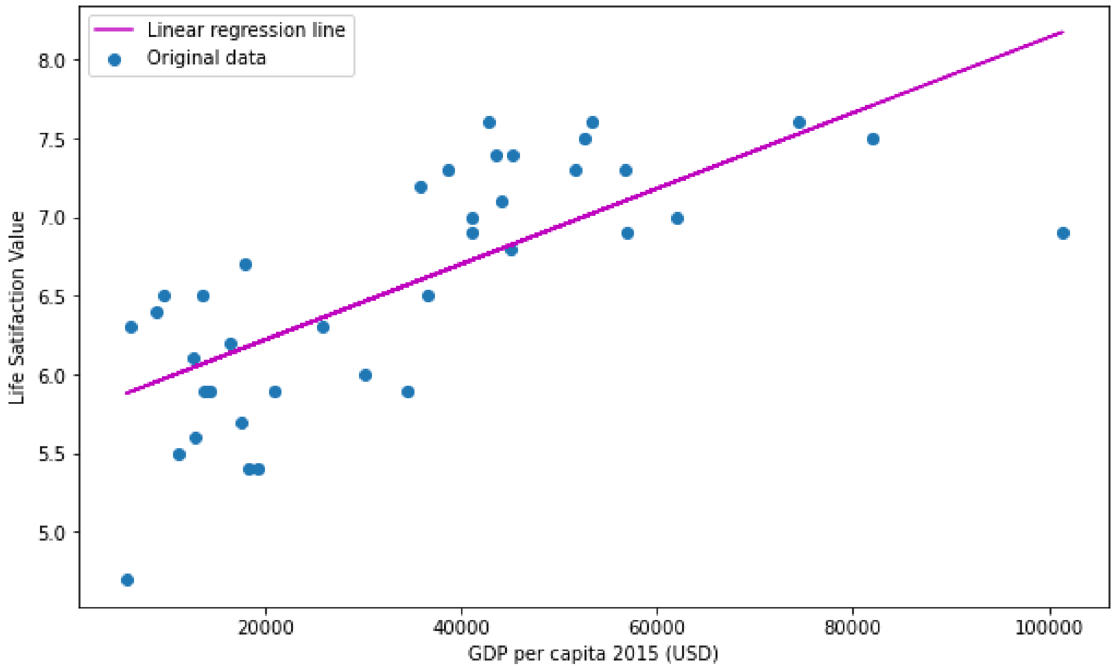
```
Model R^2 value:  0.6961783837097519
```

[125]:
```
# Here as a matter of example, I show that what I found for the simple linear␣
↪regression above
# can be done aslo by using the sklearn module as well.

model = sk.linear_model.LinearRegression(fit_intercept=True)
model.fit(X.reshape(-1, 1),y.reshape(-1, 1))
```

[125]:
```
LinearRegression()
```

[126]:
```
# I show that the sklearn module gives exactly the same results obtained above␣
↪with the stats module.

yfit = model.predict(X.reshape(-1, 1))
fig, ax=plt.subplots(figsize=(10, 6))
ax.scatter(X.reshape(-1, 1), y.reshape(-1, 1), label="Original data")
ax.plot(X.reshape(-1, 1), yfit, color="m", label="Linear regression line")
ax.set_xlabel("GDP per capita 2015 (USD)")
ax.set_ylabel("Life Satifaction Value")
ax.legend()
```

[126]:
```
<matplotlib.legend.Legend at 0x7faf4830ca90>
```



[127]:
```
# I print the values of slope and intercept coefficients for the linear model␣
↪obtained using sklearn.
# The values agree with those obtained with the stats module.

print("Model slope: ", model.coef_[0])
print("Model intercept:", model.intercept_)
```

```
Model slope:  [2.39962998e-05]
Model intercept: [5.74175435]
```

[128]:
```
# Now I make a test-train analyzis for the data in order to asses model accuracy
# in making new predictions. Here I split the data where only 20% of the data␣
↪goes into the test set.

X_train, X_test, y_train, y_test=sk.model_selection.train_test_split(X.
↪reshape(-1, 1), y.reshape(-1, 1), test_size=0.2, random_state=0)
```

[129]:
```
# To test the model accuracy of the train-test analysis, First I try the linear␣
↪regression model.

model1 = sk.linear_model.LinearRegression(fit_intercept=True)
model1.fit(X_train, y_train)
```

[129]: LinearRegression()

[130]:
```
# I print the values of the slope and intercept coefficients obtained from the
↪trainig data.

print("Model_1 slope: ", model1.coef_[0])
print("Model_1 intercept:", model1.intercept_)
```

```
Model_1 slope:  [3.08345433e-05]
Model_1 intercept: [5.54446493]
```

[131]:
```
# I print the values of the generalized correlation coefficients R^2 of the
↪train and test data of the linear regression model.

print("Model_1 train R^2 value: ", model1.score(X_train, y_train))
print("Model_1 test R^2 value: ", model1.score(X_test, y_test))
```

```
Model_1 train R^2 value:  0.589117260119626
Model_1 test R^2 value:  -0.37033956276075175
```

[132]:
```
# Second, I try the KNN regression model to test the accuracy of the train-test
↪data analysis.

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train) # I scale and fit-transform the
↪training predictor data for better stability.
X_test_scaled = scaler.transform(X_test) # I scale the test predictor data.
model2 = sk.neighbors.KNeighborsRegressor(n_neighbors=3) # I use a value of K=3
↪which gives the best model accuracy.
model2.fit(X_train_scaled, y_train)
```

[132]:
```
KNeighborsRegressor(n_neighbors=3)
```

[133]:
```
# I print the values of the generalized correlation coefficients R^2 of the
↪train and test data of the KNN regression model.

print("Model train R^2 value: ", model2.score(X_train_scaled, y_train))
print("Model test R^2 value: ", model2.score(X_test_scaled, y_test))
```

```
Model train R^2 value:  0.6880950044165277
Model test R^2 value:  0.7714814814814819
```

[134]:
```
# I create a for-loop to evaluate the RMSE and R^2 vules as a function of K to
↪test the KNN model accuracy.
# The value of K=3 gives the best model accuracy.

rmse_val = [] # I create an empty list to store the root-mean-square values of
↪the error.
```

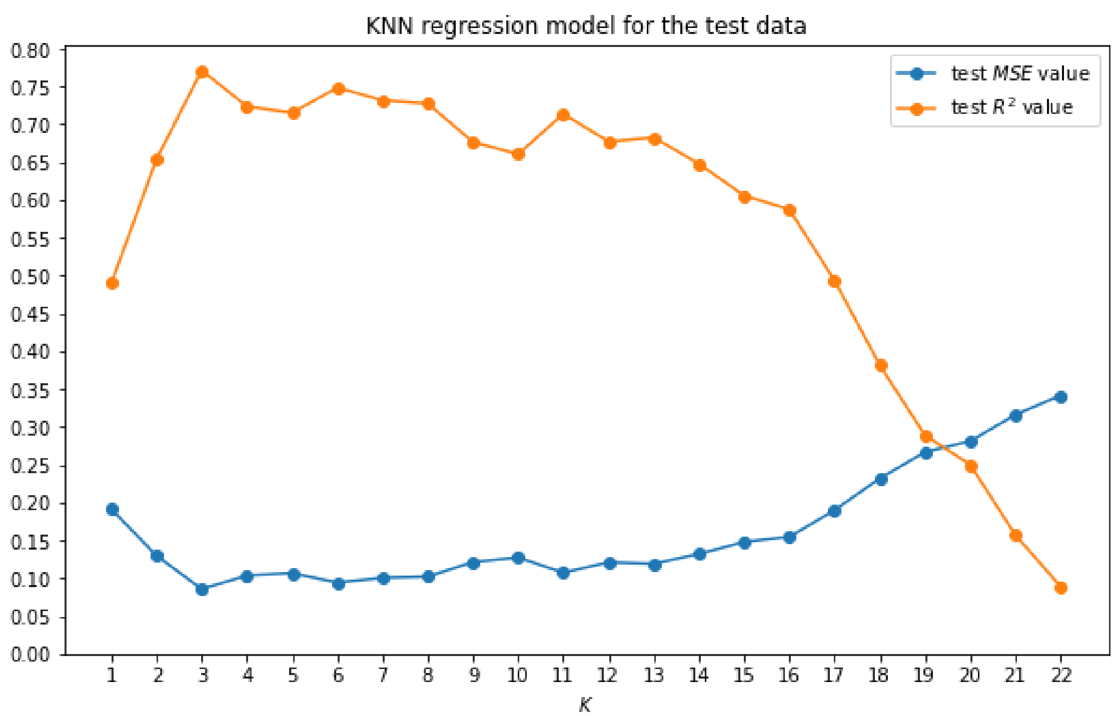
```
R_score = [] # I create an empty list to store the values of R^2 score.

for K in range(0, 22):
    K = K+1
    model3 = sk.neighbors.KNeighborsRegressor(n_neighbors = K).
 ↪fit(X_train_scaled, y_train)  #fit the model
    pred=model3.predict(X_test_scaled) # make prediction on test set
    error = np.sqrt(mean_squared_error(y_test, pred)) #calculate rmse
    rmse_val.append(error) #store rmse values
    R_score.append(model3.score(X_test_scaled, y_test))
    print('RMSE and R^2 values for k=' , K , 'are respectively:', error, model3.
 ↪score(X_test_scaled, y_test))
```

```
RMSE and R^2 values for k= 1 are respectively: 0.4373213921133974
0.4900000000000001
RMSE and R^2 values for k= 2 are respectively: 0.36012150727219816
0.6541666666666668
RMSE and R^2 values for k= 3 are respectively: 0.29273613450417124
0.7714814814814819
RMSE and R^2 values for k= 4 are respectively: 0.32198117180978103
0.7235416666666672
RMSE and R^2 values for k= 5 are respectively: 0.3267261850540906
0.7153333333333335
RMSE and R^2 values for k= 6 are respectively: 0.30709209621147127
0.7485185185185184
RMSE and R^2 values for k= 7 are respectively: 0.31719433301677885
0.7317006802721087
RMSE and R^2 values for k= 8 are respectively: 0.31957613529486195
0.7276562500000001
RMSE and R^2 values for k= 9 are respectively: 0.3482761781923885
0.6765432098765429
RMSE and R^2 values for k= 10 are respectively: 0.35677373782272703
0.6605666666666665
RMSE and R^2 values for k= 11 are respectively: 0.327635531226871
0.7137465564738292
RMSE and R^2 values for k= 12 are respectively: 0.3478605244123631
0.6773148148148151
RMSE and R^2 values for k= 13 are respectively: 0.3450302276441379
0.6825443786982248
RMSE and R^2 values for k= 14 are respectively: 0.36340053519442095
0.6478401360544223
RMSE and R^2 values for k= 15 are respectively: 0.38446933124329513
0.6058222222222222
RMSE and R^2 values for k= 16 are respectively: 0.39330331806380636
0.5875000000000007
RMSE and R^2 values for k= 17 are respectively: 0.43575591561455507
0.49364475201845515
```

```
RMSE and R^2 values for k= 18 are respectively: 0.48153400710645494
0.38166666666666793
RMSE and R^2 values for k= 19 are respectively: 0.5163933092725883
0.2889012003693463
RMSE and R^2 values for k= 20 are respectively: 0.5302534771220263
0.2502166666666682
RMSE and R^2 values for k= 21 are respectively: 0.5621670090211143
0.15724867724867808
RMSE and R^2 values for k= 22 are respectively: 0.5844268577556262
0.08918732782369299
```

[135]:
```
# I show the plot of the MSE and R^2 values vs. K values

K=np.arange(1, 23)

fig, ax=plt.subplots(figsize=(10, 6))
ax.plot(K, np.array(rmse_val)**2, label="test $MSE$ value",marker="o")
ax.plot(K, np.array(R_score), label="test $R^2$ value",marker="o")
ax.set_xlabel("$K$")
ax.set_xticks(K, minor=False)
ax.set_yticks(np.arange(0.0, 0.85, 0.05), minor=False)
ax.set_title("KNN regression model for the test data")
ax.legend()
```

[135]: <matplotlib.legend.Legend at 0x7faf48351910>



[136]:
```python
# I print the predictions of the "Life Satisfaction Values" for Albania, UAE␣
↪and Armenia using the model
# fitted with the training data for K=3.

print(model2.predict(scaler.transform(X_new)))
```

```
[[5.8       ]
 [7.06666667]
 [5.8       ]]
```