

```
[1]: #importing csv file
import pandas as pd
df=pd.read_csv('C:/Users/USER/Downloads/world-happiness-report-2021.csv')
print(df.head)

<bound method NDFrame.head of      Country name  Regional indicator  Ladder score \
0      Finland      Western Europe      7.842
1      Denmark      Western Europe      7.620
2      Switzerland  Western Europe      7.571
3      Iceland      Western Europe      7.554
4      Netherlands  Western Europe      7.464
..      ...           ...           ...
144     Lesotho     Sub-Saharan Africa      3.512
145     Botswana   Sub-Saharan Africa      3.467
146      Rwanda    Sub-Saharan Africa      3.415
147      Zimbabwe  Sub-Saharan Africa      3.145
148     Afghanistan South Asia      2.523

Standard error of ladder score  upperwhisker  lowerwhisker \
0      0.032      7.904      7.780
1      0.035      7.687      7.552
2      0.036      7.643      7.500
3      0.059      7.670      7.438
4      0.027      7.518      7.410
..      ...           ...           ...
144     0.120      3.748      3.276
145     0.074      3.611      3.322
146     0.068      3.548      3.282
147     0.058      3.259      3.030
148     0.038      2.596      2.449

Logged GDP per capita  Social support  Healthy life expectancy \
0      10.775      0.954      72.000
1      10.933      0.954      72.700
2      11.117      0.942      74.400
3      10.878      0.983      73.000
4      10.932      0.942      72.400
..      ...           ...           ...
144     7.926      0.787      48.700
145     9.782      0.784      59.269
146     7.676      0.552      61.400
147     7.943      0.750      56.201
148     7.695      0.463      52.493

Freedom to make life choices  Generosity  Perceptions of corruption \
0      0.949      -0.098      0.186
1      0.946      0.030      0.179
2      0.919      0.025      0.292
3      0.955      0.160      0.673
4      0.913      0.175      0.338
..      ...           ...           ...
144     0.715     -0.131      0.915
145     0.824     -0.246      0.801
146     0.897      0.061      0.167
147     0.677     -0.047      0.821
148     0.382     -0.102      0.924

Ladder score in Dystopia  Explained by: Log GDP per capita \
0      2.43      1.446
1      2.43      1.502
2      2.43      1.566
3      2.43      1.482
4      2.43      1.501
..      ...           ...
144     2.43      0.451
145     2.43      1.099
146     2.43      0.364
147     2.43      0.457
148     2.43      0.370

Explained by: Social support  Explained by: Healthy life expectancy \
0      1.106      0.741
1      1.108      0.763
2      1.079      0.816
3      1.172      0.772
4      1.079      0.753
..      ...           ...
144     0.731      0.007
145     0.724      0.340
146     0.202      0.407
147     0.649      0.243
148     0.000      0.126

Explained by: Freedom to make life choices  Explained by: Generosity \
0      0.091      0.124
1      0.686      0.208
2      0.653      0.204
3      0.698      0.293
4      0.647      0.302
..      ...           ...
144     0.405      0.103
145     0.539      0.027
146     0.627      0.227
147     0.359      0.157
148     0.000      0.122

Explained by: Perceptions of corruption  Dystopia + residual
0      0.481      3.253
1      0.485      2.868
2      0.413      2.839
3      0.170      2.967
4      0.384      2.798
..      ...           ...
144     0.015      1.800
145     0.088      0.648
146     0.493      1.095
147     0.075      1.205
148     0.010      1.895

[149 rows x 20 columns]>

In [2]: df.head(10)

Out[2]:
Country name  Regional indicator  Ladder score  Standard error of ladder score  upperwhisker  lowerwhisker  Logged GDP per capita  Social support  Healthy life expectancy  Freedom to make life choices  Generosity  Perceptions of corruption  Ladder score in Dystopia  Explained by: Log GDP per capita  Explained by Social support  Explained by: Healthy life expectancy  Explained by: Freedom to make life choices  Ex
0      Finland      Western Europe      7.842      0.032      7.904      7.780      10.775      0.954      72.0      0.949      -0.098      0.186      2.43      1.446      1.106      0.741      0.691
1      Denmark      Western Europe      7.620      0.035      7.687      7.552      10.933      0.954      72.7      0.946      0.030      0.179      2.43      1.502      1.108      0.763      0.686
2      Switzerland  Western Europe      7.571      0.036      7.643      7.500      11.117      0.942      74.4      0.919      0.025      0.292      2.43      1.566      1.079      0.816      0.653
3      Iceland      Western Europe      7.554      0.059      7.670      7.438      10.878      0.983      73.0      0.955      0.160      0.673      2.43      1.482      1.172      0.772      0.698
4      Netherlands  Western Europe      7.464      0.027      7.518      7.410      10.932      0.942      72.4      0.913      0.175      0.338      2.43      1.501      1.079      0.753      0.647
5      Norway      Western Europe      7.392      0.035      7.462      7.323      11.053      0.954      73.3      0.960      0.093      0.270      2.43      1.543      1.108      0.782      0.703
6      Sweden      Western Europe      7.363      0.036      7.433      7.293      10.867      0.934      72.7      0.945      0.086      0.237      2.43      1.478      1.062      0.763      0.685
7      Luxembourg  Western Europe      7.324      0.037      7.396      7.252      11.647      0.908      72.6      0.907      -0.034      0.386      2.43      1.751      1.003      0.760      0.639
8      New Zealand  North America and ANZ      7.277      0.040      7.355      7.198      10.643      0.948      73.4      0.929      0.134      0.242      2.43      1.400      1.094      0.785      0.665
9      Austria      Western Europe      7.268      0.036      7.337      7.198      10.906      0.934      73.3      0.908      0.042      0.481      2.43      1.492      1.062      0.782      0.640

In [19]: x=df[['Social support','Healthy life expectancy','Logged GDP per capita']]
y=df[['Ladder score']]

In [4]: #sklearn
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)

In [5]: x_test

Out[5]:
Social support  Healthy life expectancy  Logged GDP per capita
145      0.784      59.269      9.782
136      0.708      55.809      8.145
58      0.812      67.300      8.648
83      0.811      69.593      9.673
133      0.795      57.161      8.542
124      0.826      62.250      8.485
31      0.915      76.953      11.488
91      0.710      59.802      8.118
121      0.691      67.201      9.266
67      0.823      72.600      10.279
13      0.926      73.800      10.776
19      0.906      72.199      10.823
123      0.818      56.799      9.161
88      0.913      70.600      9.826
120      0.688      60.704      8.361
10      0.940      73.900      10.796
57      0.879      72.600      10.421
49      0.905      66.701      10.008
23      0.898      69.600      10.871
101      0.639      55.008      7.838
135      0.569      54.914      7.362
82      0.636      58.221      8.117
34      0.882      66.601      9.577
131      0.750      61.998      9.367
111      0.776      59.962      9.603
113      0.765      62.000      8.360
138      0.603      60.633      8.755
80      0.817      67.102      10.238
51      0.847      68.001      9.557
16      0.934      72.500      10.707
56      0.898      69.000      9.962
54      0.864      67.657      8.620
147      0.750      56.201      7.943
143      0.537      57.948      6.958
86      0.774      64.233      8.120
65      0.821      68.800      9.313
66      0.893      64.401      8.538
8      0.948      73.400      10.643
85      0.799      67.055      9.487
148      0.463      52.493      7.695
144      0.787      48.700      7.926
87      0.931      67.000      10.016
59      0.924      70.799      10.217
106      0.861      66.700      9.073
6      0.934      72.700      10.867

In [6]: len(x_test)

Out[6]: 45

In [7]: from sklearn.linear_model import LinearRegression
lin_reg=LinearRegression()
lin_reg.fit(x_train,y_train)

Out[7]: LinearRegression()

In [8]: y_pred=lin_reg.predict(x_test)

In [9]: print(lin_reg.predict([[0.820,73.898,10.576]]))

[6.24814531]

In [10]: from sklearn.metrics import r2_score
r2_score(y_test,y_pred)

Out[10]: 0.627604563161883

In [11]: from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.linear_model import LinearRegression

In [12]: df.dropna

Out[12]:
<bound method DataFrame.dropna of      Country name  Regional indicator  Ladder score \
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Logged GDP per capita  Social support  Healthy life expectancy \
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148     7.695      0.463      52.493

Freedom to make life choices  Generosity  Perceptions of corruption \
0      0.949      -0.098      0.186
1      0.946      0.030      0.179
2      0.919      0.025      0.292
3      0.955      0.160      0.673
4      0.913      0.175      0.338
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Explained by: Social support  Explained by: Healthy life expectancy \
0      1.106      0.741
1      1.108      0.763
2      1.079      0.816
3      1.172      0.772
4      1.079      0.753
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1      0.485      2.868
2      0.413      2.839
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144     0.015      1.800
145     0.088      0.648
146     0.493      1.095
147     0.075      1.205
148     0.010      1.895

[149 rows x 20 columns]>

In [13]: print(x_test)

Social support  Healthy life expectancy  Logged GDP per capita
145      0.784      59.269      9.782
136      0.708      55.809      8.145
58      0.812      67.300      8.648
83      0.811      69.593      9.673
133      0.795      57.161      8.542
124      0.826      62.250      8.485
31      0.915      76.953      11.488
91      0.710      59.802      8.118
121      0.691      67.201      9.266
67      0.823      72.600      10.279
13      0.926      73.800      10.776
19      0.906      72.199      10.823
123      0.818      56.799      9.161
88      0.913      70.600      9.826
120      0.688      60.704      8.361
10      0.940      73.900      10.796
57      0.879      72.600      10.421
49      0.905      66.701      10.008
23      0.898      69.600      10.871
135      0.569      55.008      7.838
101      0.639      54.914      7.362
82      0.636      58.221      8.117
34      0.882      66.601      9.577
131      0.750      61.998      9.367
111      0.776      59.962      9.603
113      0.765      62.000      8.360
138      0.603      60.633      8.755
80      0.817      67.102      10.238
51      0.847      68.001      9.557
16      0.934      72.500      10.707
56      0.898      69.000      9.962
54      0.864      67.657      8.620
147      0.750      56.201      7.943
143      0.537      57.948      6.958
86      0.774      64.233      8.120
65      0.821      68.800      9.313
66      0.893      64.401      8.538
8      0.948      73.400      10.643
85      0.799      67.055      9.487
148      0.463      52.493      7.695
144      0.787      48.700      7.926
87      0.931      67.000      10.016
59      0.924      70.799      10.217
106      0.861      66.700      9.073
6      0.934      72.700      10.867

In [14]: print(y_train)

4      7.464
141      3.623
4      7.554
98      5.045
70      5.653
14      7.085
41      6.179
0      7.842
137      3.849
50      6.032
Name: Ladder score, Length: 104, dtype: float64

In [15]: print('Linear Regression:')
print()
reg = LinearRegression()
reg.fit(x_train, y_train)
y_pred = reg.predict(x_test)

Linear Regression:

In [16]: import numpy as np

In [17]: print('Accuracy:',reg.score(x_train, y_train)*100)
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
sns.scatterplot(y_pred, y_test)

Accuracy: 69.61484679234361
Mean Absolute Error: 0.58581321208044657
Mean Squared Error: 0.49550853270716077
Root Mean Squared Error: 0.7039179872024587

In [18]: from sklearn.ensemble import RandomForestRegressor
print('Random Forest Regressor')
print()
rfr = RandomForestRegressor()
rfr.fit(x_train,y_train)
y_pred = rfr.predict(x_test)
print('Accuracy:',rfr.score(x_test, y_test)*100)
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

Random Forest Regressor:

Accuracy: 67.54786802249924
Mean Absolute Error: 0.58581321208044657
Mean Squared Error: 0.49550853270716077
Root Mean Squared Error: 0.7039179872024587

In [ ]:
```