In [331]:
```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
```

In [332]:
```python
data = pd.read_csv("2018.csv")
```

In [333]:
```python
data
```

Out[333]:

| | Overall rank | Country or region | Score | GDP per capita | Social support | Healthy life expectancy | Freedom to make life choices | Generosity | Perceptions of corruption |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | Finland | 7.632 | 1.305 | 1.592 | 0.874 | 0.681 | 0.202 | 0.393 |
| **1** | 2 | Norway | 7.594 | 1.456 | 1.582 | 0.861 | 0.686 | 0.286 | 0.340 |
| **2** | 3 | Denmark | 7.555 | 1.351 | 1.590 | 0.868 | 0.683 | 0.284 | 0.408 |
| **3** | 4 | Iceland | 7.495 | 1.343 | 1.644 | 0.914 | 0.677 | 0.353 | 0.138 |
| **4** | 5 | Switzerland | 7.487 | 1.420 | 1.549 | 0.927 | 0.660 | 0.256 | 0.357 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | .. |
| **151** | 152 | Yemen | 3.355 | 0.442 | 1.073 | 0.343 | 0.244 | 0.083 | 0.064 |
| **152** | 153 | Tanzania | 3.303 | 0.455 | 0.991 | 0.381 | 0.481 | 0.270 | 0.097 |
| **153** | 154 | South Sudan | 3.254 | 0.337 | 0.608 | 0.177 | 0.112 | 0.224 | 0.106 |
| **154** | 155 | Central African Republic | 3.083 | 0.024 | 0.000 | 0.010 | 0.305 | 0.218 | 0.038 |
| **155** | 156 | Burundi | 2.905 | 0.091 | 0.627 | 0.145 | 0.065 | 0.149 | 0.076 |

156 rows × 9 columns

In [334]:
```
data.describe()
```

Out[334]:

| | Overall rank | Score | GDP per capita | Social support | Healthy life expectancy | Freedom to make life choices | Generosity | Pe c |
|---|---|---|---|---|---|---|---|---|
| **count** | 156.000000 | 156.000000 | 156.000000 | 156.000000 | 156.000000 | 156.000000 | 156.000000 | [illegible] |
| **mean** | 78.500000 | 5.375917 | 0.891449 | 1.213237 | 0.597346 | 0.454506 | 0.181006 | |
| **std** | 45.177428 | 1.119506 | 0.391921 | 0.302372 | 0.247579 | 0.162424 | 0.098471 | |
| **min** | 1.000000 | 2.905000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | 0.000000 | |
| **25%** | 39.750000 | 4.453750 | 0.616250 | 1.066750 | 0.422250 | 0.356000 | 0.109500 | |
| **50%** | 78.500000 | 5.378000 | 0.949500 | 1.255000 | 0.644000 | 0.487000 | 0.174000 | |
| **75%** | 117.250000 | 6.168500 | 1.197750 | 1.463000 | 0.777250 | 0.578500 | 0.239000 | |
| **max** | 156.000000 | 7.632000 | 2.096000 | 1.644000 | 1.030000 | 0.724000 | 0.598000 | |

In [335]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 156 entries, 0 to 155
Data columns (total 9 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Overall rank                  156 non-null    int64  
 1   Country or region             156 non-null    object 
 2   Score                         156 non-null    float64
 3   GDP per capita                156 non-null    float64
 4   Social support                156 non-null    float64
 5   Healthy life expectancy       156 non-null    float64
 6   Freedom to make life choices  156 non-null    float64
 7   Generosity                    156 non-null    float64
 8   Perceptions of corruption     155 non-null    float64
dtypes: float64(7), int64(1), object(1)
memory usage: 11.1+ KB
```

In [336]:
```
data.corr()
```

Out[336]:

| | Overall rank | Score | GDP per capita | Social support | Healthy life expectancy | Freedom to make life choices | Generosity | Perc co |
|---|---|---|---|---|---|---|---|---|
| **Overall rank** | 1.000000 | -0.991749 | -0.805897 | -0.737500 | -0.778700 | -0.530786 | -0.103602 | -0 |
| **Score** | -0.991749 | 1.000000 | 0.802124 | 0.745760 | 0.775814 | 0.544280 | 0.135825 | 0 |
| **GDP per capita** | -0.805897 | 0.802124 | 1.000000 | 0.672080 | 0.844273 | 0.332275 | -0.011241 | 0 |
| **Social support** | -0.737500 | 0.745760 | 0.672080 | 1.000000 | 0.667288 | 0.411087 | 0.018226 | 0 |
| **Healthy life expectancy** | -0.778700 | 0.775814 | 0.844273 | 0.667288 | 1.000000 | 0.355475 | 0.020751 | 0 |
| **Freedom to make life choices** | -0.530786 | 0.544280 | 0.332275 | 0.411087 | 0.355475 | 1.000000 | 0.297988 | 0 |
| **Generosity** | -0.103602 | 0.135825 | -0.011241 | 0.018226 | 0.020751 | 0.297988 | 1.000000 | 0 |
| **Perceptions of corruption** | -0.371133 | 0.405292 | 0.319582 | 0.218364 | 0.315569 | 0.462446 | 0.362249 | 1 |

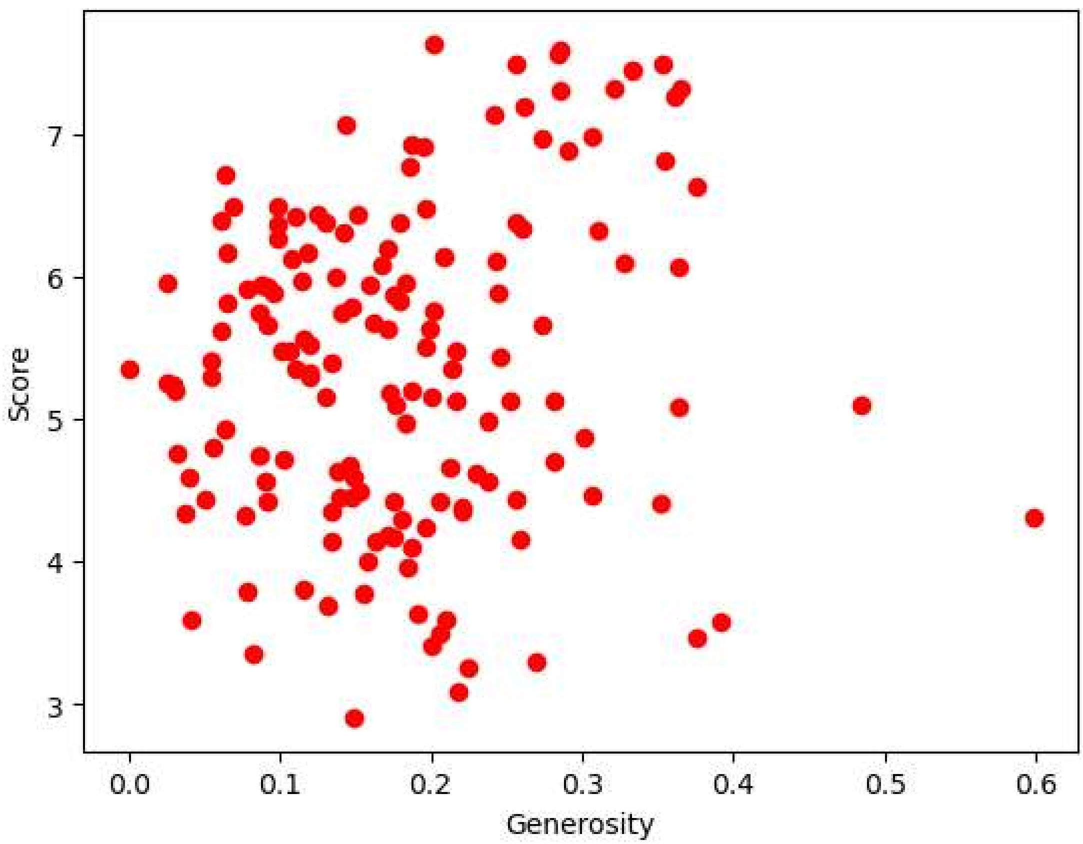
In [337]:
```
x = data['Generosity']
x
```

Out[337]:
```
0      0.202
1      0.286
2      0.284
3      0.353
4      0.256
       ...
151    0.083
152    0.270
153    0.224
154    0.218
155    0.149
Name: Generosity, Length: 156, dtype: float64
```

In [338]:
```
y = data['Score']
y
```

Out[338]:
```
0      7.632
1      7.594
2      7.555
3      7.495
4      7.487
       ...
151    3.355
152    3.303
153    3.254
154    3.083
155    2.905
Name: Score, Length: 156, dtype: float64
```

In [339]:
```
plt.scatter(x,y, c='red')
plt.xlabel("Generosity")
plt.ylabel("Score")
plt.show()
```




In [340]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y, test_size = 0.2, ran
```

In [341]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(124,)
(32,)
(124,)
(32,)
```

In [342]:
```
x_train = x_train.values.reshape(-1,1)
```

In [343]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

In [344]:
```
x_test = x_test.values.reshape(-1,1)
```

In [345]:
```
model.fit(x_test,y_test)
model.score(x_test,y_test)
```

Out[345]:
```
0.01623481625805867
```

In [346]:
```
print(f"Intercept: {model.intercept_}")
print(f"Slope: {model.coef_}")
```

```
Intercept: 5.013574253181054
Slope: [1.80400933]
```

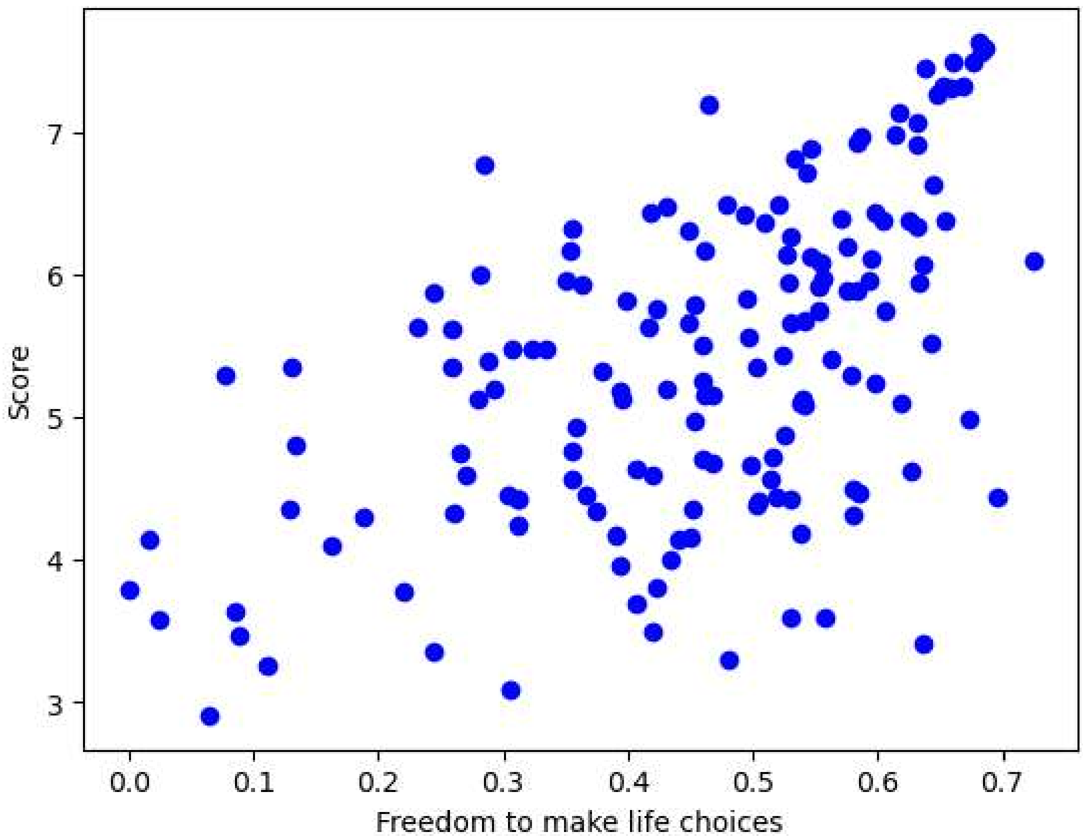
In [347]:
```
y_pred = model.intercept_ + model.coef_*x_test
print(f"y_pred \n: {y_pred}")
```

```
y_pred
: [[5.26433155]
 [5.45736055]
 [5.17232707]
 [5.47540064]
 [5.26974358]
 [5.38880819]
 [5.5060688 ]
 [5.4284964 ]
 [5.15609099]
 [5.39241621]
 [5.37437612]
 [5.01357425]
 [5.40324027]
 [5.37618013]
 [5.24809547]
 [5.61430936]
 [5.64858554]
 [5.36716008]
 [5.34911999]
 [5.33649192]
 [5.32927589]
 [5.25170348]
 [5.2931957 ]
 [5.12903085]
 [5.46998861]
 [5.22283934]
 [5.3328839 ]
 [5.45194852]
 [5.38520017]
 [5.31484381]
 [5.52230488]
 [5.29860773]]
```

In [348]:
```
x1= data['Freedom to make life choices']
x1
```

Out[348]:
```
0      0.681
1      0.686
2      0.683
3      0.677
4      0.660
       ...
151    0.244
152    0.481
153    0.112
154    0.305
155    0.065
Name: Freedom to make life choices, Length: 156, dtype: float64
```

In [349]:
```
plt.scatter(x1,y,c='blue')
plt.xlabel('Freedom to make life choices')
plt.ylabel('Score')
plt.show()
```




In [350]:
```
x1_train, x1_test, y_train, y_test = train_test_split(x1,y,test_size=0.2,rand
```

In [351]:
```
print(x1_train.shape)
print(x1_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(124,)
(32,)
(124,)
(32,)
```

In [352]:
```
x1_test = x1_test.values.reshape(-1,1)
```

In [353]:
```
model1 = LinearRegression()
model1.fit(x1_test,y_test)
model1.score(x1_test,y_test)
```

Out[353]:
```
0.05897612626358284
```

In [354]:
```python
print(f"Intercept is: {model1.intercept_}")
print(f"Slope is: {model1.coef_}")
```

```
Intercept is: 4.443215240751754
Slope is: [1.90004003]
```

In [355]:
```python
y1_pred = model1.intercept_ + model1.coef_*x1_test
print(f"y1_pred: {y1_pred}")
```

```
y1_pred: [[5.14052993]
 [5.43883622]
 [5.44643638]
 [5.68584142]
 [5.29633322]
 [5.44453634]
 [5.5566387 ]
 [5.6326403 ]
 [5.49393738]
 [5.4521365 ]
 [5.6516407 ]
 [4.69212048]
 [4.97522645]
 [5.32103374]
 [5.33243398]
 [5.65544078]
 [5.40083542]
 [5.64404054]
 [4.98282661]
 [5.59083942]
 [4.90682501]
 [5.21463149]
 [4.86312409]
 [5.12532961]
 [5.19373105]
 [5.3856351 ]
 [5.61743998]
 [5.57183902]
 [5.4521365 ]
 [5.49583742]
 [5.31533362]
 [5.26783261]]
```

In [356]:
```
xmulti = data.iloc[:,3:6]
xmulti
```

Out[356]:

| | GDP per capita | Social support | Healthy life expectancy |
|---|---|---|---|
| **0** | 1.305 | 1.592 | 0.874 |
| **1** | 1.456 | 1.582 | 0.861 |
| **2** | 1.351 | 1.590 | 0.868 |
| **3** | 1.343 | 1.644 | 0.914 |
| **4** | 1.420 | 1.549 | 0.927 |
| **...** | ... | ... | ... |
| **151** | 0.442 | 1.073 | 0.343 |
| **152** | 0.455 | 0.991 | 0.381 |
| **153** | 0.337 | 0.608 | 0.177 |
| **154** | 0.024 | 0.000 | 0.010 |
| **155** | 0.091 | 0.627 | 0.145 |

156 rows × 3 columns

In [357]:
```
xmulti_train, xmulti_test, y_train, y_test = train_test_split(xmulti, y, test_
```

In [358]:
```
print(xmulti_train.shape)
print(xmulti_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(124, 3)
(32, 3)
(124,)
(32,)
```

In [359]:
```
modelm = LinearRegression()
modelm.fit(xmulti_test,y_test)
modelm.score(xmulti_test,y_test)
```

Out[359]: 0.7667812201092875

In [360]:
```
print(f"Intercept: {modelm.intercept_}")
print(f"slope: {modelm.coef_}")
```

```
Intercept: 2.5683505615348445
slope: [ 1.52319243  1.14897506 -0.01656893]
```

In [362]:
```
ym_pred = modelm.intercept_ + modelm.coef_*xmulti_test
print(f"ym_pred is : {ym_pred}")
```

```
ym_pred is :      GDP per capita  Social support  Healthy life expectancy
117       3.131932        3.985037                 2.565832
75        4.708436        4.050528                 2.551285
51        4.268233        3.968951                 2.556322
31        5.080095        4.065465                 2.555957
35        4.473864        4.335474                 2.552362
40        3.585843        4.083849                 2.556752
14        4.609428        4.261940                 2.554085
109       3.665049        3.756391                 2.561044
53        4.539362        4.248152                 2.551980
146       2.851664        3.189946                 2.563280
150       3.074050        3.597832                 2.561723
78        4.326115        3.949419                 2.553786
92        3.962072        3.806946                 2.555791
90        3.617830        3.914949                 2.567555
89        3.820415        4.021804                 2.557664
5         4.641415        4.278025                 2.553803
123       3.319284        3.772476                 2.560828
16        4.968902        4.314793                 2.553505
19        5.760962        3.459955                 2.557249
29        3.757964        4.025251                 2.558277
56        4.496712        3.951717                 2.552527
143       3.112130        3.825329                 2.564241
142       2.967427        3.611620                 2.561690
99        4.173795        4.309048                 2.556553
93        3.960548        4.311346                 2.558823
69        4.068695        4.119467                 2.559188
94        3.657433        4.136702                 2.556719
42        4.606382        4.137850                 2.556785
122       2.869943        3.604726                 2.565484
44        4.813536        4.063167                 2.557167
105       4.181411        3.454210                 2.556901
138       2.962857        3.112965                 2.564159
```