In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.ensemble import RandomForestRegressor
from sklearn.tree import DecisionTreeRegressor
```

In [2]:
```
df = pd.read_csv("Crime Economics - data.csv")
df
```

Out[2]:

	Country	Crime Rate	Unemployment (%)	HDI	Population Density (per sq. km)	Weapons per 100 persons	Per Capita Income	Gini Coefficient	Litera R
0	Afghanistan	76.31	11.2	0.51	57.00	12.5	508.00	27.8	0
1	Albania	42.53	11.3	0.80	100.00	12.0	5,181.00	33.2	0
2	Algeria	52.03	11.5	0.75	18.00	2.1	3,368.00	27.6	0
3	Argentina	63.82	7.0	0.85	16.00	7.4	8,476.00	41.4	0
4	Armenia	22.79	7.7	0.78	99.00	6.1	4,266.00	34.4	1
...	...	...	...	...	...	...	...	...	
109	Uzbekistan	33.42	8.9	0.72	73.00	0.4	1,724.00	39.7	1
110	Venezuela	83.76	9.4	0.71	32.00	18.5	3,740.00	46.9	0
111	Vietnam	46.19	8.8	0.70	289.00	1.6	2,786.00	35.7	0
112	Zambia	43.62	11.4	0.58	23.00	0.9	985.00	57.1	0
113	Zimbabwe	59.30	5.0	0.57	37.00	2.8	1,466.00	44.3	0

114 rows × 10 columns

In [3]:
```
df.head()
```

Out[3]:

	Country	Crime Rate	Unemployment (%)	HDI	Population Density (per sq. km)	Weapons per 100 persons	Per Capita Income	Gini Coefficient	Literacy Rate
0	Afghanistan	76.31	11.2	0.51	57.00	12.5	508.00	27.8	0.38
1	Albania	42.53	11.3	0.80	100.00	12.0	5,181.00	33.2	0.98
2	Algeria	52.03	11.5	0.75	18.00	2.1	3,368.00	27.6	0.80
3	Argentina	63.82	7.0	0.85	16.00	7.4	8,476.00	41.4	0.98
4	Armenia	22.79	7.7	0.78	99.00	6.1	4,266.00	34.4	1.00

In [4]:
```
df.tail()
```

Out[4]:

	Country	Crime Rate	Unemployment (%)	HDI	Population Density (per sq. km)	Weapons per 100 persons	Per Capita Income	Gini Coefficient	Litera Ra
109	Uzbekistan	33.42	8.9	0.72	73.00	0.4	1,724.00	39.7	1.
110	Venezuela	83.76	9.4	0.71	32.00	18.5	3,740.00	46.9	0.
111	Vietnam	46.19	8.8	0.70	289.00	1.6	2,786.00	35.7	0.
112	Zambia	43.62	11.4	0.58	23.00	0.9	985.00	57.1	0.
113	Zimbabwe	59.30	5.0	0.57	37.00	2.8	1,466.00	44.3	0.

In [5]:
```
df.describe()
```

Out[5]:

	Crime Rate	Unemployment (%)	HDI	Weapons per 100 persons	Gini Coefficient	Literacy Rate	Happiness Index
count	114.000000	114.000000	114.000000	114.00000	114.000000	114.000000	114.000000
mean	44.498421	7.743860	0.782456	12.35000	37.091754	0.899912	5.748333
std	14.220020	5.642052	0.122609	14.30866	9.578128	0.138765	1.025004
min	15.230000	0.700000	0.490000	0.00000	0.360000	0.380000	2.520000
25%	33.420000	4.200000	0.712500	2.85000	31.425000	0.837500	5.045000
50%	44.715000	6.400000	0.780000	9.25000	35.050000	0.960000	5.845000
75%	54.212500	9.825000	0.890000	16.65000	42.125000	0.990000	6.367500
max	83.760000	35.300000	0.960000	120.50000	69.300000	1.000000	7.840000

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 114 entries, 0 to 113
Data columns (total 10 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Country                        114 non-null    object 
 1   Crime Rate                     114 non-null    float64
 2   Unemployment (%)               114 non-null    float64
 3   HDI                            114 non-null    float64
 4   Population Density (per sq. km)  114 non-null    object 
 5   Weapons per 100 persons        114 non-null    float64
 6   Per Capita Income              114 non-null    object 
 7   Gini Coefficient               114 non-null    float64
 8   Literacy Rate                  114 non-null    float64
 9   Happiness Index                114 non-null    float64
dtypes: float64(7), object(3)
memory usage: 9.0+ KB
```

In [7]:
```
df.dtypes
```

Out[7]:
```
Country                            object
Crime Rate                        float64
Unemployment (%)                  float64
HDI                               float64
Population Density (per sq. km)    object
Weapons per 100 persons           float64
Per Capita Income                  object
Gini Coefficient                  float64
Literacy Rate                     float64
Happiness Index                   float64
dtype: object
```

In [8]:
```
df['Population Density (per sq. km)'] = df['Population Density (per sq. km)']
```

In [9]:
```
df['Per Capita Income'] = df['Per Capita Income'].str.replace(',', '').astype
```

In [10]:
```
df
```

Out[10]:

	Country	Crime Rate	Unemployment (%)	HDI	Population Density (per sq. km)	Weapons per 100 persons	Per Capita Income	Gini Coefficient	Litera Ra
0	Afghanistan	76.31	11.2	0.51	57.0	12.5	508.0	27.8	0.:
1	Albania	42.53	11.3	0.80	100.0	12.0	5181.0	33.2	0.!
2	Algeria	52.03	11.5	0.75	18.0	2.1	3368.0	27.6	0.8
3	Argentina	63.82	7.0	0.85	16.0	7.4	8476.0	41.4	0.!
4	Armenia	22.79	7.7	0.78	99.0	6.1	4266.0	34.4	1.(
...	...	...	...	...	...	...	...	...	
109	Uzbekistan	33.42	8.9	0.72	73.0	0.4	1724.0	39.7	1.(
110	Venezuela	83.76	9.4	0.71	32.0	18.5	3740.0	46.9	0.!
111	Vietnam	46.19	8.8	0.70	289.0	1.6	2786.0	35.7	0.!
112	Zambia	43.62	11.4	0.58	23.0	0.9	985.0	57.1	0.(
113	Zimbabwe	59.30	5.0	0.57	37.0	2.8	1466.0	44.3	0.8

114 rows × 10 columns

In [11]:
```
df.dtypes
```

Out[11]:
```
Country                              object
Crime Rate                          float64
Unemployment (%)                    float64
HDI                                 float64
Population Density (per sq. km)     float64
Weapons per 100 persons             float64
Per Capita Income                   float64
Gini Coefficient                    float64
Literacy Rate                       float64
Happiness Index                     float64
dtype: object
```

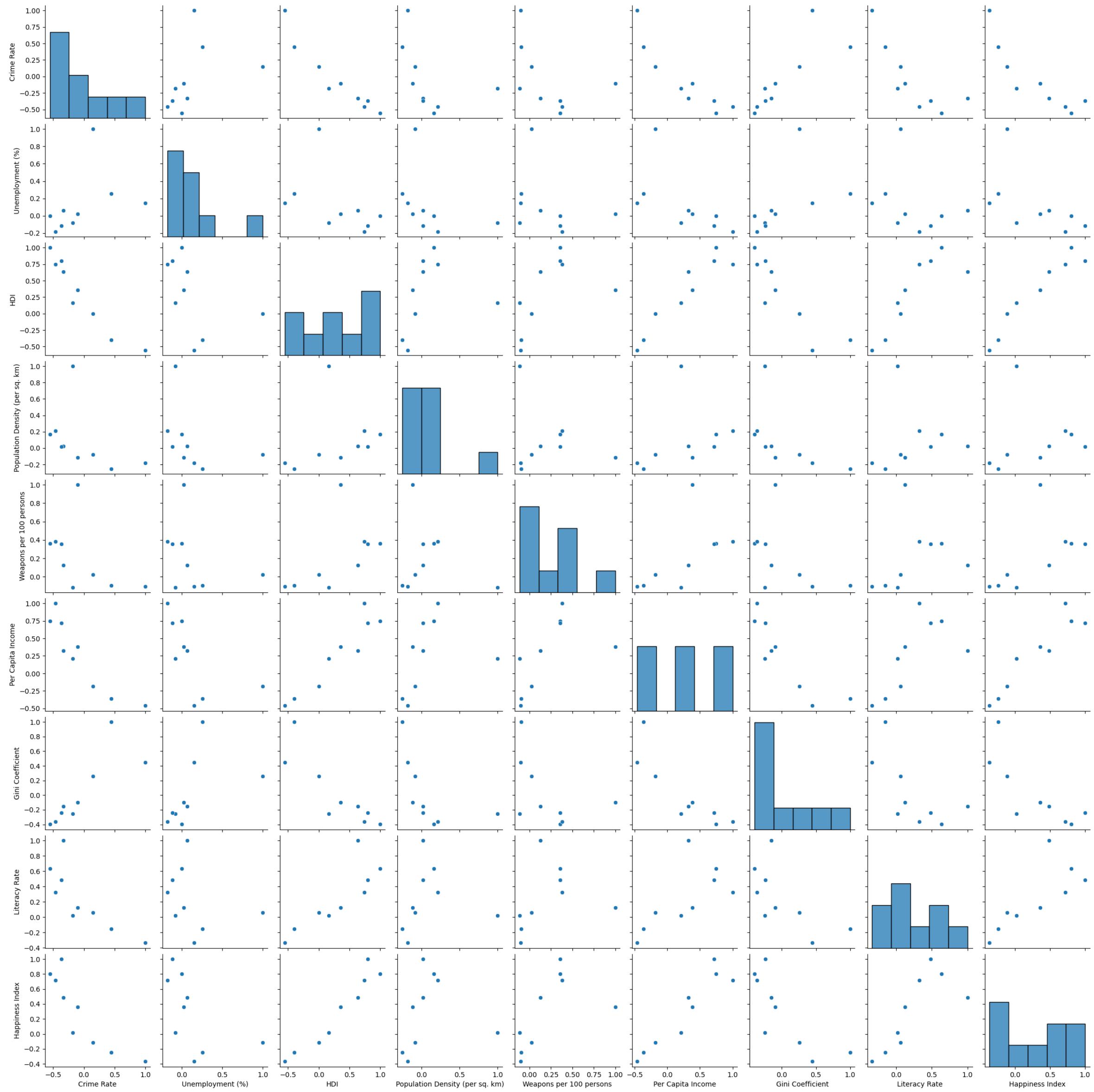
In [12]:
```
df.index
```

Out[12]:
```
RangeIndex(start=0, stop=114, step=1)
```

In [13]:
```
corr = df.corr()
```

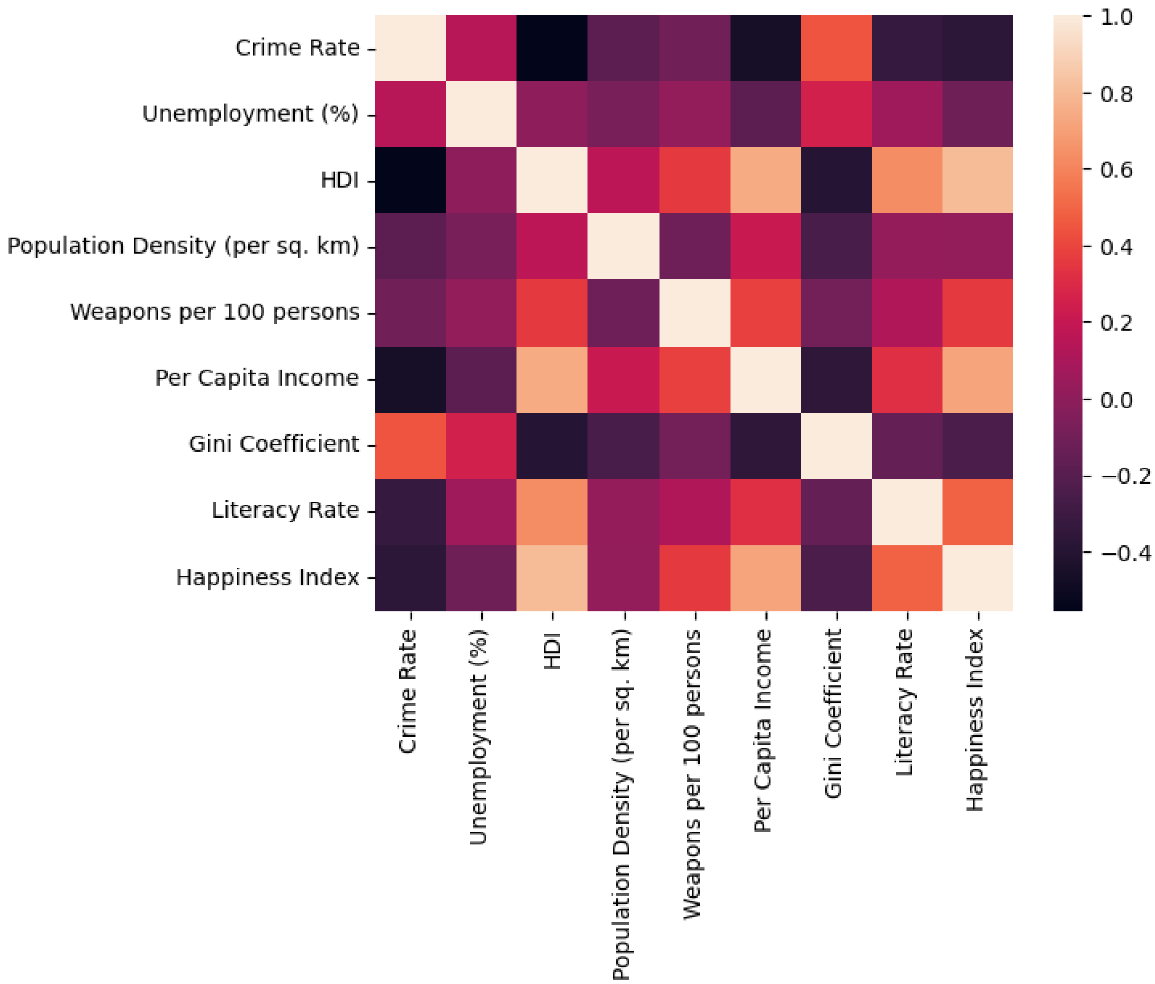
In [14]:
```
sns.pairplot(corr)
```

Out[14]: <seaborn.axisgrid.PairGrid at 0x1a73481d040>



In [15]:
```
sns.heatmap(corr)
```

Out[15]: <AxesSubplot:>



In [16]:
```
df.columns
```

Out[16]:
```
Index(['Country', 'Crime Rate', 'Unemployment (%)', 'HDI',
       'Population Density (per sq. km)', 'Weapons per 100 persons',
       'Per Capita Income', 'Gini Coefficient', 'Literacy Rate',
       'Happiness Index'],
      dtype='object')
```

In [17]:
```
for column in df.columns:
    unique = df[column].unique()
    print(f"Unique values in {column}:")
    print(unique)
```

```
Unique values in Country:
['Afghanistan' 'Albania' 'Algeria' 'Argentina' 'Armenia' 'Australia'
 'Austria' 'Azerbaijan' 'Bangladesh' 'Belarus' 'Belgium' 'Bolivia'
 'Bosnia and Herzegovina' 'Brazil' 'Bulgaria' 'Cambodia' 'Cameroon'
 'Canada' 'Chile' 'China' 'Colombia' 'Costa Rica' 'Croatia' 'Cyprus'
 'Czech Republic' 'Denmark' 'Dominican Republic' 'Ecuador' 'Egypt'
 'El Salvador' 'Estonia' 'Ethiopia' 'Finland' 'France' 'Georgia' 'Germany'
 'Ghana' 'Greece' 'Guatemala' 'Honduras' 'Hong Kong' 'Hungary' 'Iceland'
 'India' 'Indonesia' 'Iran' 'Iraq' 'Ireland' 'Israel' 'Italy' 'Jamaica'
 'Japan' 'Jordan' 'Kazakhstan' 'Kenya' 'Kyrgyzstan' 'Latvia' 'Lebanon'
 'Libya' 'Lithuania' 'Luxembourg' 'Malaysia' 'Maldives' 'Malta'
 'Mauritius' 'Mexico' 'Moldova' 'Mongolia' 'Montenegro' 'Morocco'
 'Myanmar' 'Namibia' 'Nepal' 'Netherlands' 'New Zealand' 'Nicaragua'
 'Nigeria' 'North Macedonia' 'Norway' 'Pakistan' 'Panama' 'Paraguay'
 'Peru' 'Philippines' 'Poland' 'Portugal' 'Romania' 'Russia' 'Rwanda'
 'Saudi Arabia' 'Serbia' 'Singapore' 'Slovakia' 'Slovenia' 'South Africa'
 'South Korea' 'Spain' 'Sri Lanka' 'Sweden' 'Switzerland' 'Tanzania'
 'Thailand' 'Tunisia' 'Turkey' 'Uganda' 'Ukraine' 'United Arab Emirates'
 'United States' 'Uruguay' 'Uzbekistan' 'Venezuela' 'Vietnam' 'Zambia'
 'Zimbabwe']
Unique values in Crime Rate:
[76.31 42.53 52.03 63.82 22.79 43.03 25.54 32.02 63.9  59.58 44.58 57.77
 42.99 67.49 38.21 51.13 65.24 41.89 53.42 30.14 56.87 54.22 24.59 31.28
 25.52 26.22 61.02 55.23 46.83 67.79 23.71 49.3  27.59 51.99 23.38 35.79
 46.98 45.85 58.67 74.54 22.   34.36 23.75 44.43 45.93 49.38 48.42 45.51
 31.47 44.85 67.42 22.19 39.96 53.77 60.14 38.77 46.77 61.78 33.42 34.13
 57.29 55.34 40.39 48.88 54.19 46.35 56.01 41.18 48.66 46.51 65.21 36.01
 27.16 42.88 47.89 64.06 39.12 33.72 42.51 45.15 49.37 66.72 42.46 30.5
 29.91 28.3  39.99 24.89 25.23 38.1  27.96 30.37 22.28 76.86 26.68 33.32
 41.39 48.   21.62 56.   39.35 43.69 39.62 56.12 47.42 15.23 47.81 51.73
 83.76 46.19 43.62 59.3 ]
Unique values in Unemployment (%):
[11.2 11.3 11.5  7.   7.7  7.1  5.7  6.   4.2  4.6  5.3  3.5 18.4  2.9
  4.7  0.7  3.4  6.9 10.4  6.7 14.2 22.   7.5  9.4  9.3  5.9  4.9  6.8
  1.5  8.4 11.9 20.4  5.4  1.   5.2  6.4  7.2  7.9 12.8  1.9 10.7  1.6
 14.6  5.   2.6  6.6  8.5  6.3 18.6  9.6  2.5  3.9 30.   3.8  2.   5.6
 12.7  1.7 23.   7.4  2.7  4.4 16.4 10.   3.1 14.   7.3  3.6 35.3 13.3
  8.9  5.1 16.2  9.9  2.4 11.1  8.8 11.4]
Unique values in HDI:
[0.51 0.8  0.75 0.85 0.78 0.94 0.92 0.76 0.63 0.82 0.93 0.72 0.77 0.59
 0.56 0.81 0.89 0.9  0.71 0.67 0.49 0.95 0.61 0.66 0.65 0.96 0.73 0.83
 0.6  0.7  0.87 0.74 0.88 0.69 0.58 0.54 0.86 0.53 0.57]
Unique values in Population Density (per sq. km):
[5.700e+01 1.000e+02 1.800e+01 1.600e+01 9.900e+01 3.000e+00 1.060e+02
 1.150e+02 1.087e+03 4.600e+01 3.760e+02 1.000e+01 6.500e+01 2.500e+01
 6.400e+01 9.000e+01 5.300e+01 4.000e+00 1.490e+02 4.300e+01 9.800e+01
 7.300e+01 1.290e+02 1.350e+02 1.330e+02 2.210e+02 6.700e+01 3.050e+02
 2.900e+01 1.180e+02 2.330e+02 1.250e+02 8.000e+01 1.580e+02 8.500e+01
 6.677e+03 1.040e+02 4.110e+02 1.400e+02 5.000e+01 8.800e+01 6.900e+01
 4.310e+02 2.010e+02 2.670e+02 3.370e+02 1.120e+02 7.000e+00 8.700e+01
 3.200e+01 3.000e+01 6.560e+02 2.340e+02 9.500e+01 1.719e+03 1.390e+03
 6.440e+02 1.200e+02 2.000e+00 4.500e+01 8.100e+01 7.900e+01 1.910e+02
 4.570e+02 2.120e+02 2.410e+02 5.500e+01 1.700e+01 3.560e+02 1.220e+02
 1.110e+02 8.200e+01 9.000e+00 4.670e+02 8.041e+03 1.020e+02 4.700e+01
 5.110e+02 9.200e+01 3.240e+02 2.200e+01 2.070e+02 5.900e+01 7.100e+01
 1.050e+02 1.770e+02 3.400e+01 2.000e+01 2.890e+02 2.300e+01 3.700e+01]
Unique values in Weapons per 100 persons:
```

```
[ 12.5  12.    2.1   7.4   6.1  14.5  30.    3.6   0.4  12.7   2.   31.2
   8.3   8.4   4.5  34.7  12.1  10.1  10.   13.7  34.    9.9   2.4   4.1
   5.   32.4  19.6   8.   17.6  14.1  10.5  31.7   5.3   0.    7.3   7.2
   6.7  14.4   8.8   0.3  18.7   2.8   1.5  31.9  13.3  13.6  18.9   0.7
   6.2  28.3  12.9   3.    7.9  39.1   4.8   1.6  15.4   2.6  26.3   5.2
   3.2  29.8  28.8  22.3  10.8  16.7   2.5  21.3  12.3   0.5   6.5  15.6
   9.7   0.2   7.5  23.1  27.6   0.8  15.1   1.1  16.5 120.5  18.5   0.9]
Unique values in Per Capita Income:
[   508.   5181.   3368.   8476.   4266.  55823.  48106.   4202.   2001.
   6377.  45028.   3133.   6035.   6797.  10058.   1513.   1502.  43560.
  13232.  10229.   5333.  12077.  13934.  28133.  22911.  61477.   7268.
   5600.   3609.   3799.  23106.    840.  48685.  38959.   3984.  45909.
   2206.  18117.   4332.   2406.  46611.  16129.  63644.   1931.   3870.
  11183.   4146.  86251.  47034.  31238.   4665.  39990.   4283.   9111.
   1879.   1186.  17871.   9310.   4243.  20772. 117182.  10402.   6924.
  33771.   8587.   8326.   2954.   4007.   7626.   3108.   1292.   4215.
   1135.  53334.  43972.   1905.   2085.   5886.  66871.   1167.  12269.
   4950.   6163.   3299.  15764.  22413.  12929.  10166.    798.  20110.
   7656.  58114.  19264.  25777.   5094.  31947.  27409.   3768.  53575.
  86919.   1115.   7189.   3318.   8538.    846.   3557.  36285.  63123.
  15438.   1724.   3740.   2786.    985.   1466.]
Unique values in Gini Coefficient:
[27.8  33.2  27.6  41.4  34.4  29.7  26.6  32.4  25.2  27.4  42.2  33.
 53.3  40.4  69.2  46.6  33.8  44.4  38.5  50.4  48.   30.4  31.4  24.9
 28.7  43.7  45.4  31.5  38.6  35.   31.6  36.4  31.9  43.5  48.3  52.1
 46.7  30.6  26.8  37.8  39.   40.8  29.5  32.8  35.9  45.5  32.9  33.7
 27.5  27.7  35.6  31.8  69.3  37.3  34.9  41.   31.3  29.2  36.8  25.7
 32.7  39.5  30.7  59.1  28.5  32.5  46.2  35.1  34.2  27.   33.5  49.2
 42.8  36.   37.5  54.1  36.2   0.36 24.2  63.   34.7  39.8  28.8  40.5
 41.9  26.1  34.8  39.7  46.9  35.7  57.1  44.3 ]
Unique values in Literacy Rate:
[0.38 0.98 0.8  1.   0.99 0.76 0.96 0.92 0.77 0.75 0.97 0.95 0.79 0.68
 0.74 0.49 0.89 0.94 0.87 0.44 0.78 0.91 0.66 0.39 0.82 0.65 0.83 0.6
 0.59 0.71 0.93 0.86 0.63]
Unique values in Happiness Index:
[2.52 5.12 4.89 5.93 5.28 7.18 7.27 5.17 5.03 5.53 6.83 5.72 5.81 6.33
 5.27 4.83 5.14 7.1  6.17 5.34 6.01 7.07 5.88 6.22 6.97 7.62 5.55 5.76
 4.28 6.06 6.19 7.84 6.69 7.16 5.09 6.44 5.92 5.48 5.99 7.55 3.82 5.35
 4.72 4.85 7.09 6.48 6.31 5.94 4.4  6.15 4.61 5.74 6.03 4.58 5.41 6.26
 7.32 5.38 5.2  6.6  6.05 6.32 5.77 5.68 5.58 4.92 4.43 4.57 7.46 7.28
 5.97 4.76 5.1  7.39 4.93 6.18 5.65 5.84 6.14 3.42 6.49 6.08 6.38 6.46
 4.96 5.85 4.33 7.36 7.57 3.62 4.6  4.95 4.64 4.88 6.56 6.95 6.43 4.07
 3.15]
```

In [18]:
```
df.isnull()
```

Out[18]:

	Country	Crime Rate	Unemployment (%)	HDI	Population Density (per sq. km)	Weapons per 100 persons	Per Capita Income	Gini Coefficient	Literacy Rate
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
109	False	False	False	False	False	False	False	False	False
110	False	False	False	False	False	False	False	False	False
111	False	False	False	False	False	False	False	False	False
112	False	False	False	False	False	False	False	False	False
113	False	False	False	False	False	False	False	False	False

114 rows × 10 columns

In [19]:
```
df.isnull().sum()
```

Out[19]:
```
Country                          0
Crime Rate                       0
Unemployment (%)                 0
HDI                              0
Population Density (per sq. km)  0
Weapons per 100 persons          0
Per Capita Income                0
Gini Coefficient                 0
Literacy Rate                    0
Happiness Index                  0
dtype: int64
```

In [20]:
```
df.isna()
```

Out[20]:

	Country	Crime Rate	Unemployment (%)	HDI	Population Density (per sq. km)	Weapons per 100 persons	Per Capita Income	Gini Coefficient	Literacy Rate
0	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...
109	False	False	False	False	False	False	False	False	False
110	False	False	False	False	False	False	False	False	False
111	False	False	False	False	False	False	False	False	False
112	False	False	False	False	False	False	False	False	False
113	False	False	False	False	False	False	False	False	False

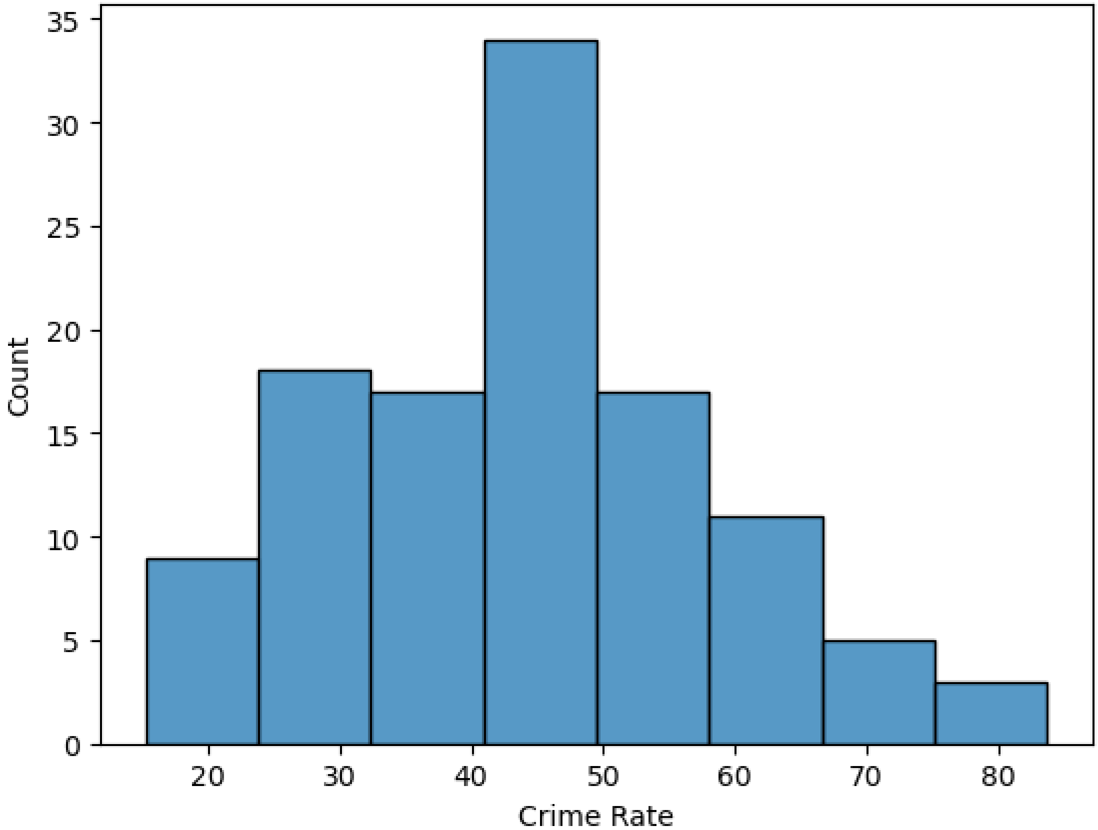
114 rows × 10 columns

In [21]:
```
df.isna().sum()
```

Out[21]:
```
Country                           0
Crime Rate                        0
Unemployment (%)                  0
HDI                               0
Population Density (per sq. km)   0
Weapons per 100 persons           0
Per Capita Income                 0
Gini Coefficient                  0
Literacy Rate                     0
Happiness Index                   0
dtype: int64
```

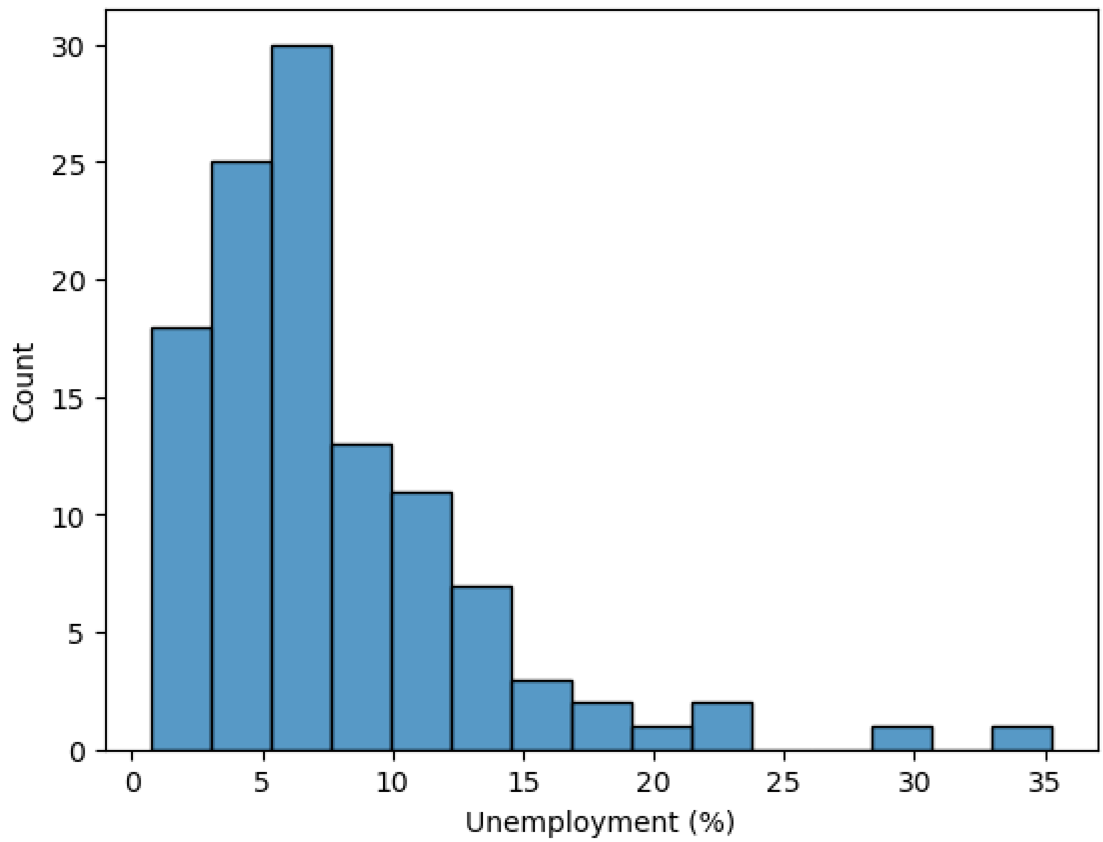
In [22]:
```
sns.histplot(x = df['Crime Rate'], data=df)
```

Out[22]: <AxesSubplot:xlabel='Crime Rate', ylabel='Count'>



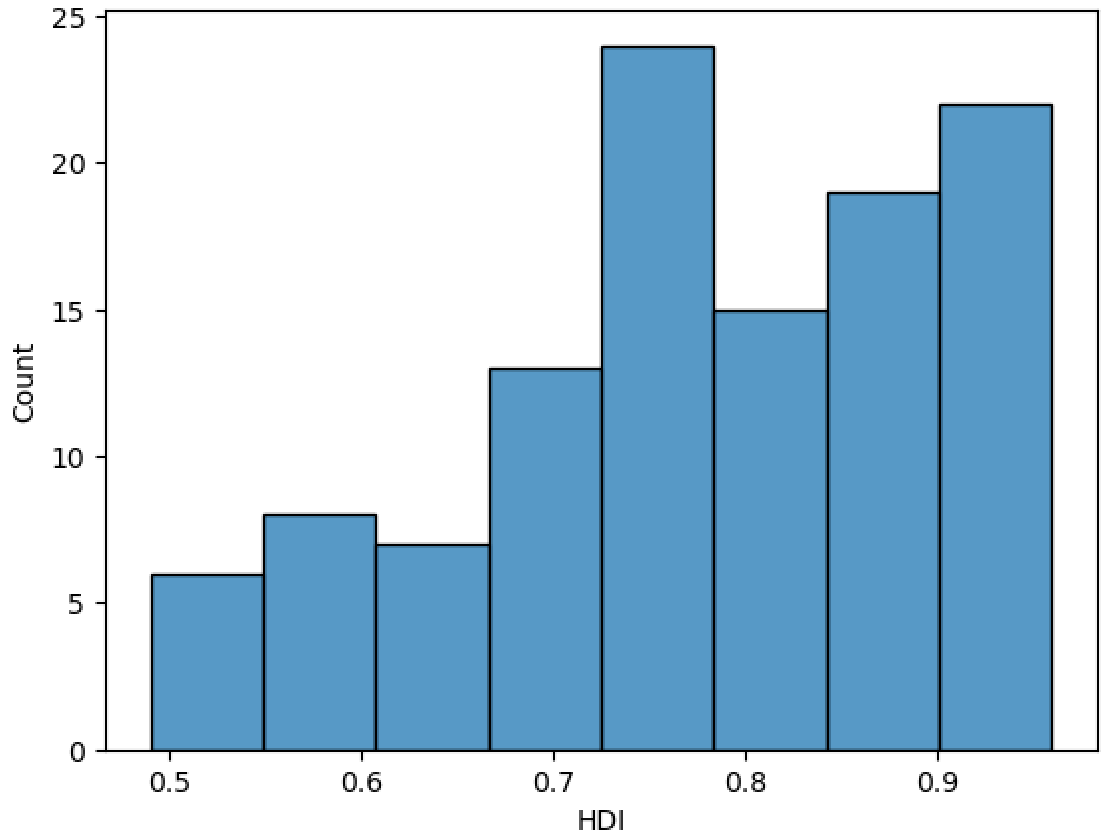
In [23]:
```
sns.histplot(x = df['Unemployment (%)'], data=df)
```

Out[23]:
```
<AxesSubplot:xlabel='Unemployment (%)', ylabel='Count'>
```



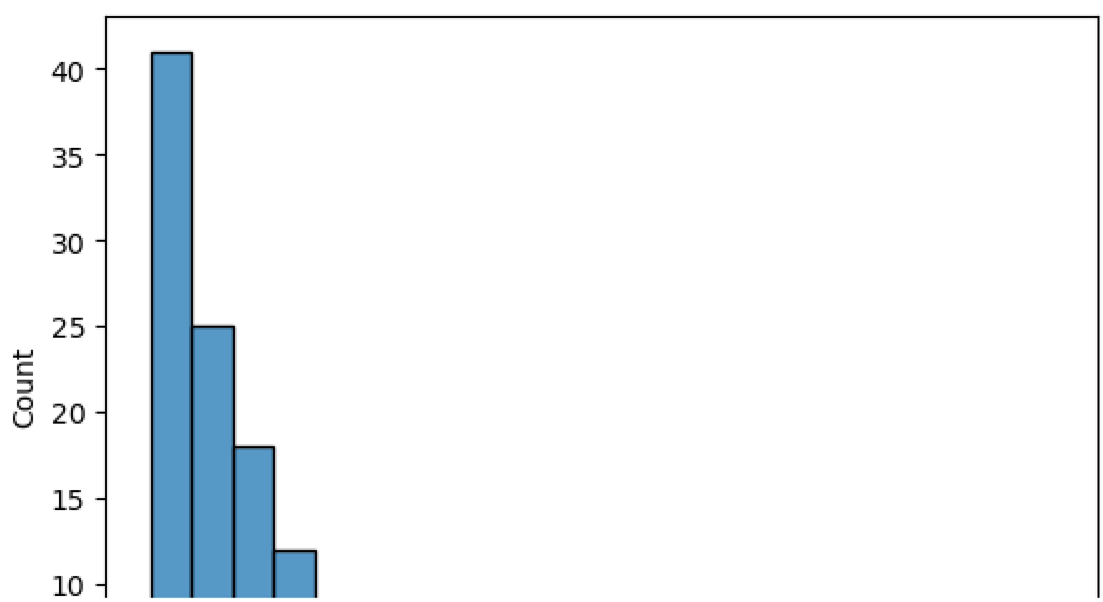
In [24]:
```
sns.histplot(x = df['HDI'], data=df)
```

Out[24]: <AxesSubplot:xlabel='HDI', ylabel='Count'>



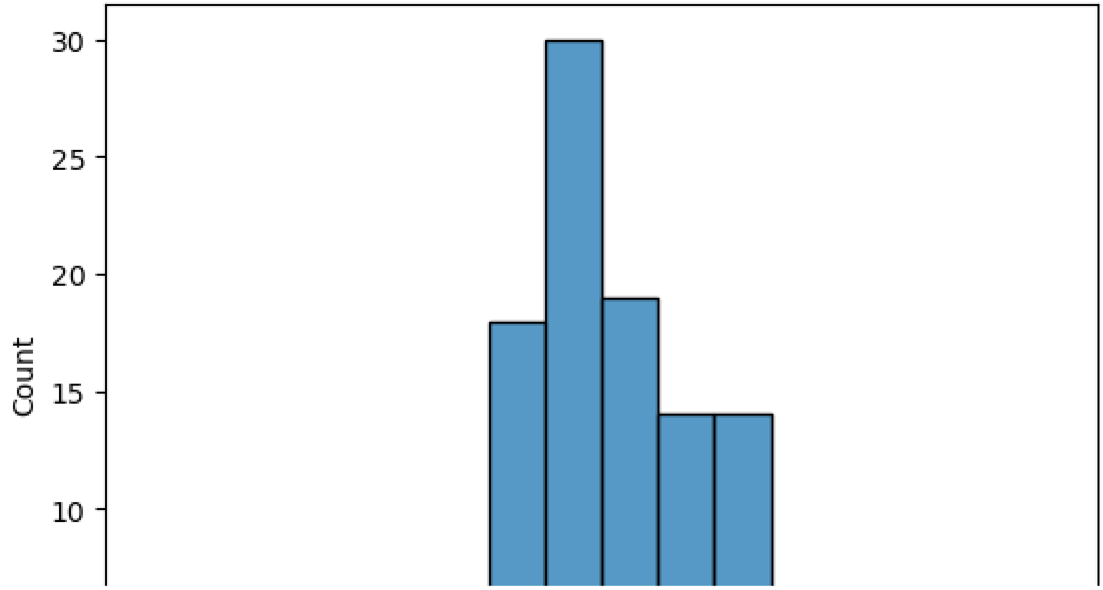
In [25]:
```
sns.histplot(x = df['Weapons per 100 persons'], data=df)
```

Out[25]: <AxesSubplot:xlabel='Weapons per 100 persons', ylabel='Count'>



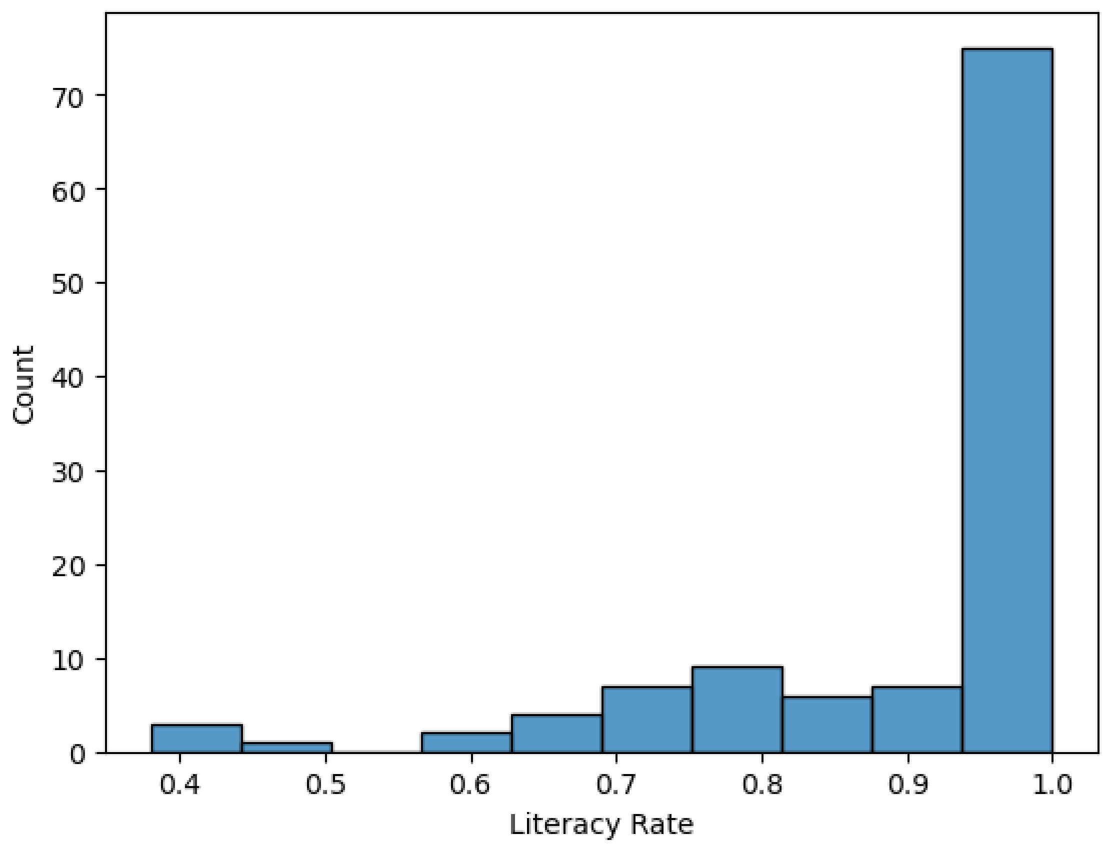
In [26]:
```
sns.histplot(x = df['Gini Coefficient'], data=df)
```

Out[26]: <AxesSubplot:xlabel='Gini Coefficient', ylabel='Count'>



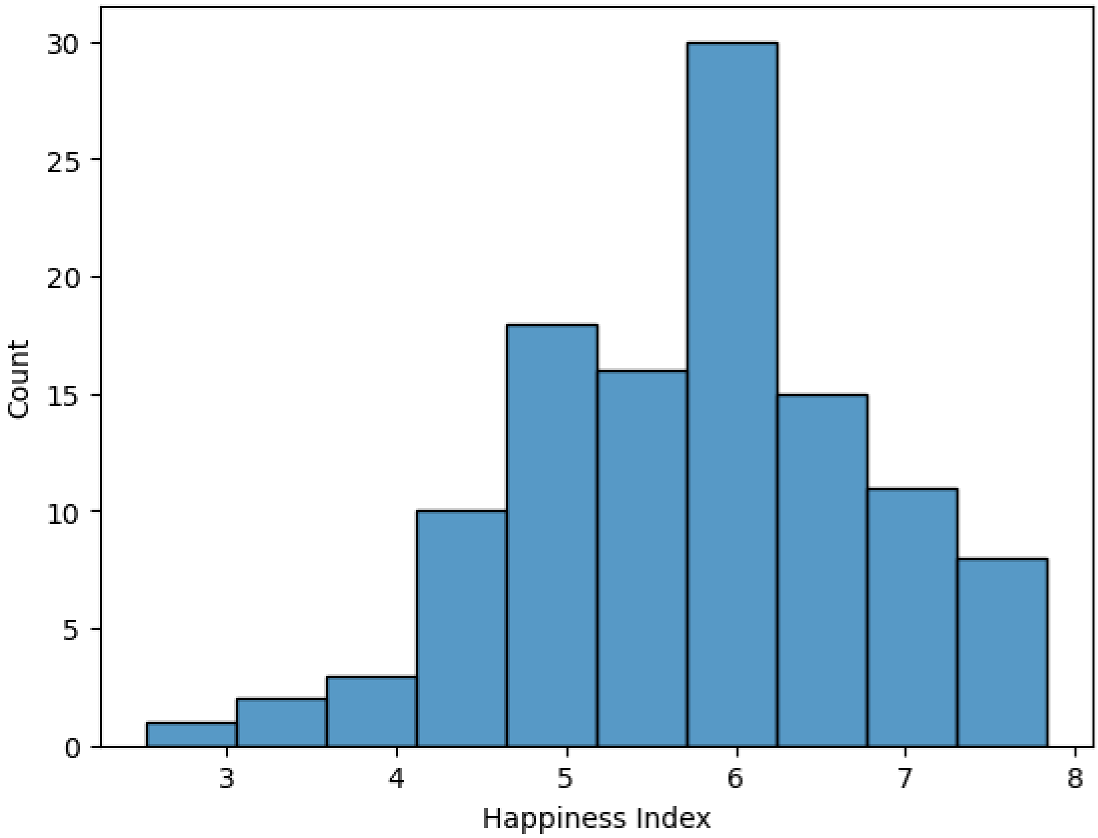
In [27]:
```
sns.histplot(x = df['Literacy Rate'], data=df)
```

Out[27]: <AxesSubplot:xlabel='Literacy Rate', ylabel='Count'>

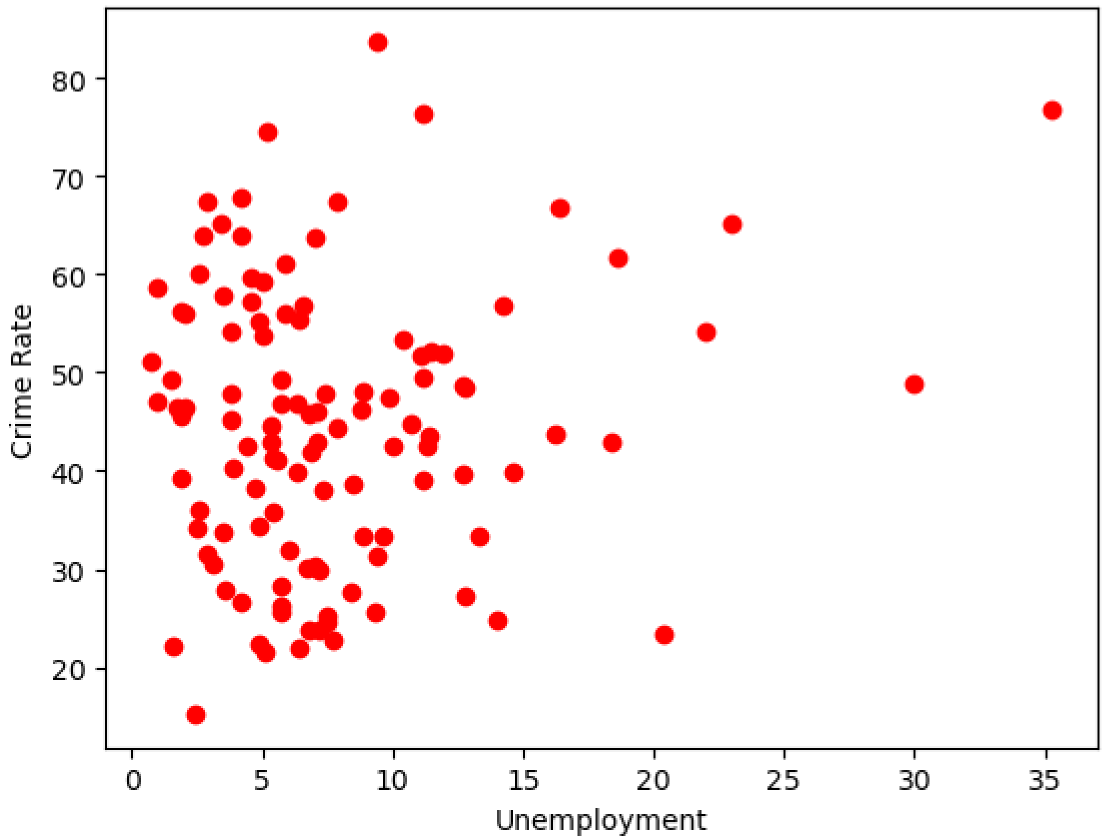


In [28]:
```
sns.histplot(x = df['Happiness Index'], data=df)
```

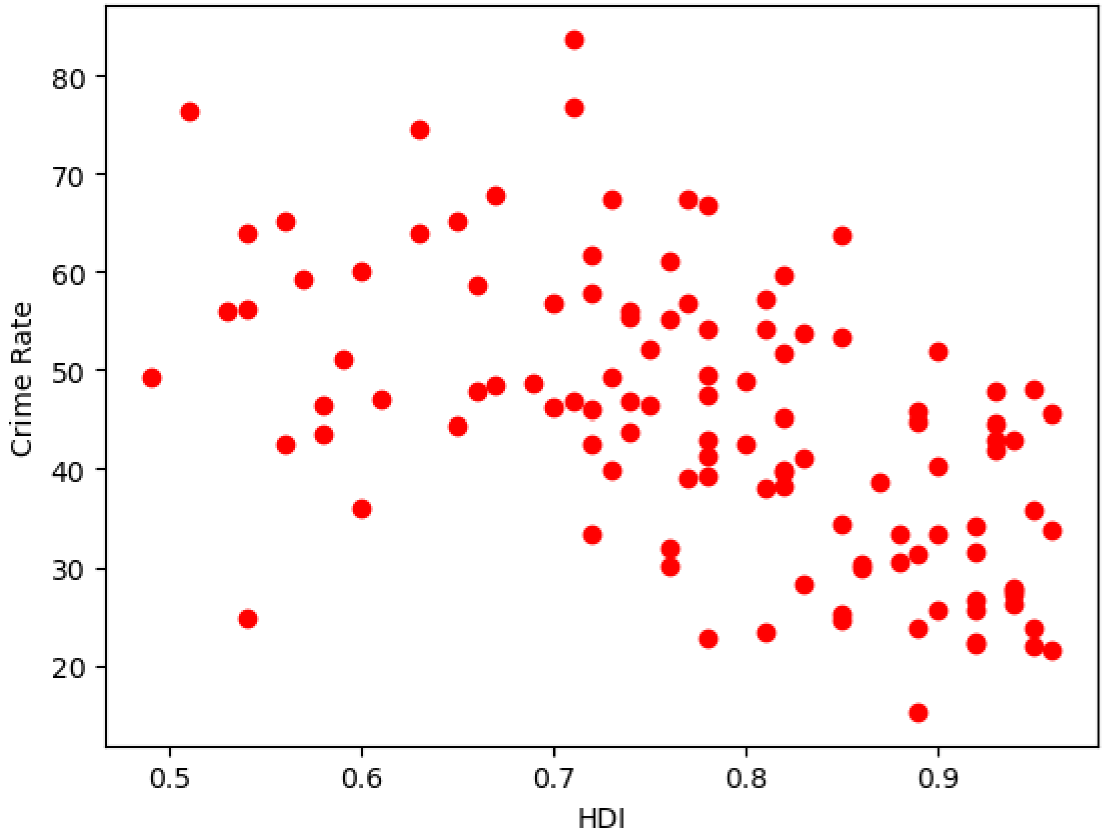
Out[28]: <AxesSubplot:xlabel='Happiness Index', ylabel='Count'>



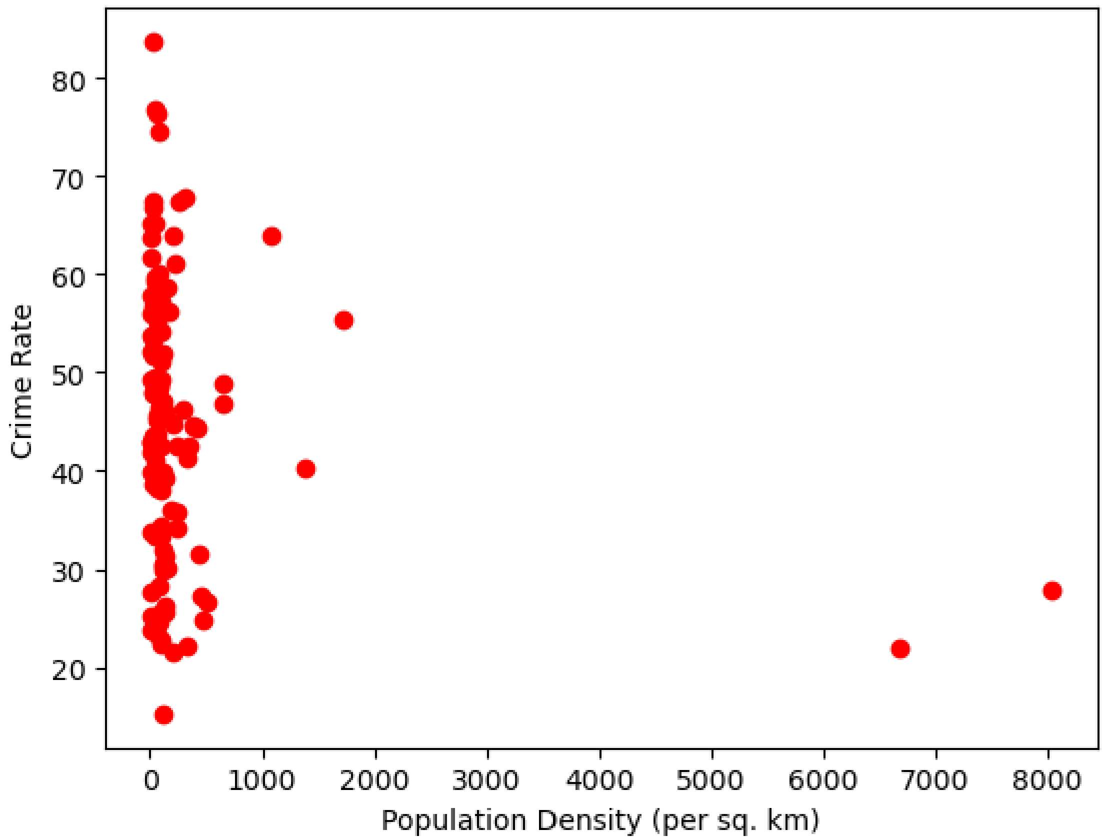
In [29]:
```
plt.scatter(x = df['Unemployment (%)'], y = df['Crime Rate'], c='r')
plt.xlabel("Unemployment")
plt.ylabel("Crime Rate")
plt.show()
```



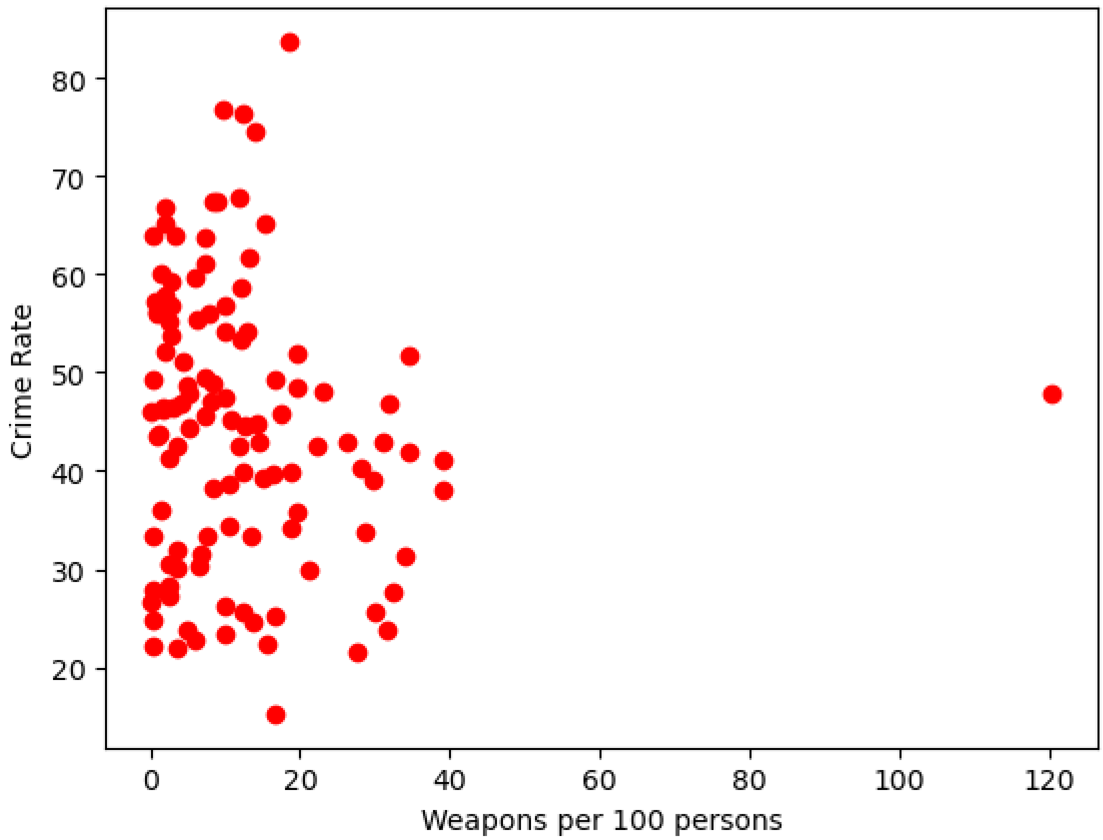
In [30]:
```
plt.scatter(x = df['HDI'], y = df['Crime Rate'], c='r')
plt.xlabel("HDI")
plt.ylabel("Crime Rate")
plt.show()
```



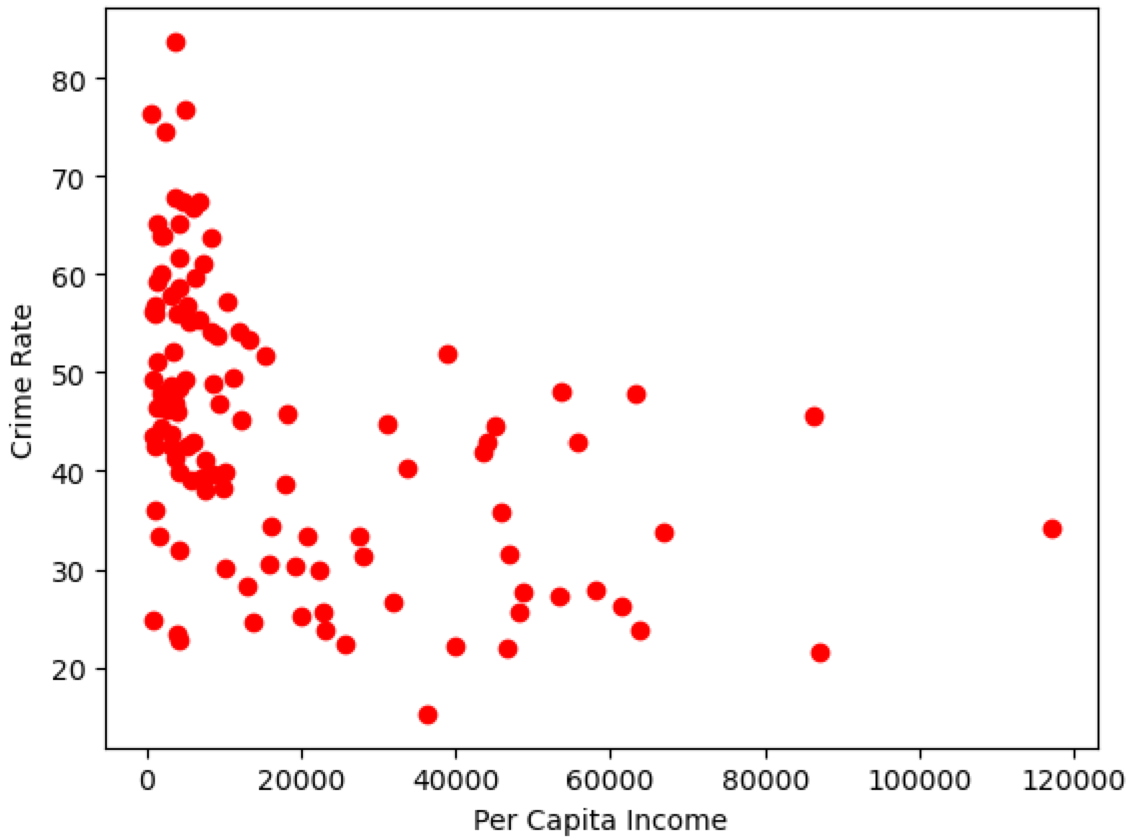
In [31]:
```
plt.scatter(x = df['Population Density (per sq. km)'], y = df['Crime Rate'], 
plt.xlabel("Population Density (per sq. km)")
plt.ylabel("Crime Rate")
plt.show()
```



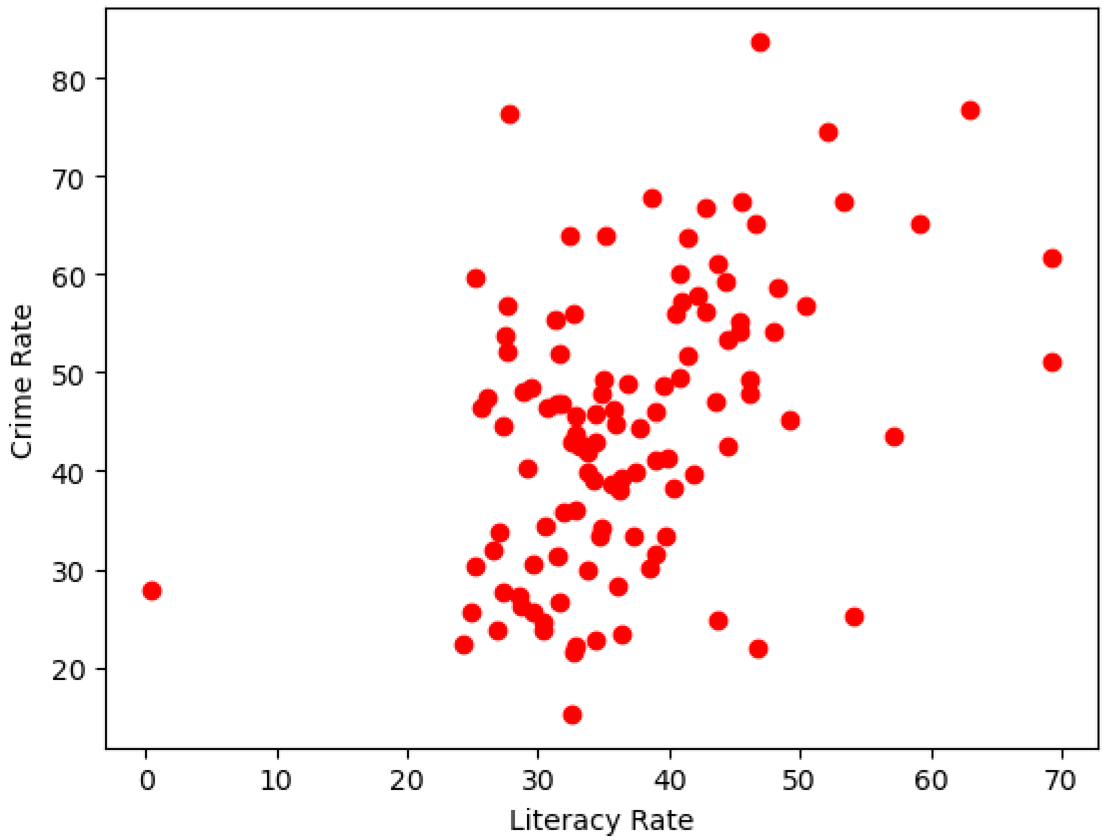
In [32]:
```
plt.scatter(x = df['Weapons per 100 persons'], y = df['Crime Rate'], c='r')
plt.xlabel("Weapons per 100 persons")
plt.ylabel("Crime Rate")
plt.show()
```



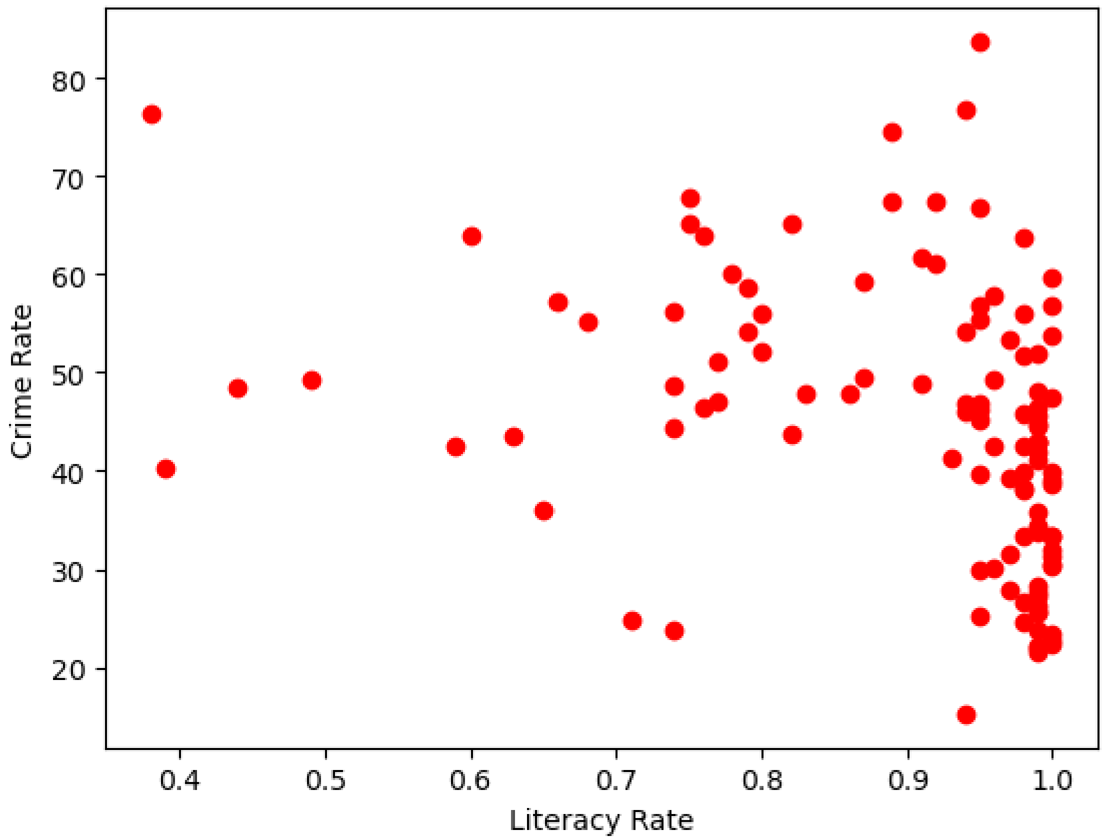
In [33]:
```
plt.scatter(x = df['Per Capita Income'], y = df['Crime Rate'], c='r')
plt.xlabel("Per Capita Income")
plt.ylabel("Crime Rate")
plt.show()
```



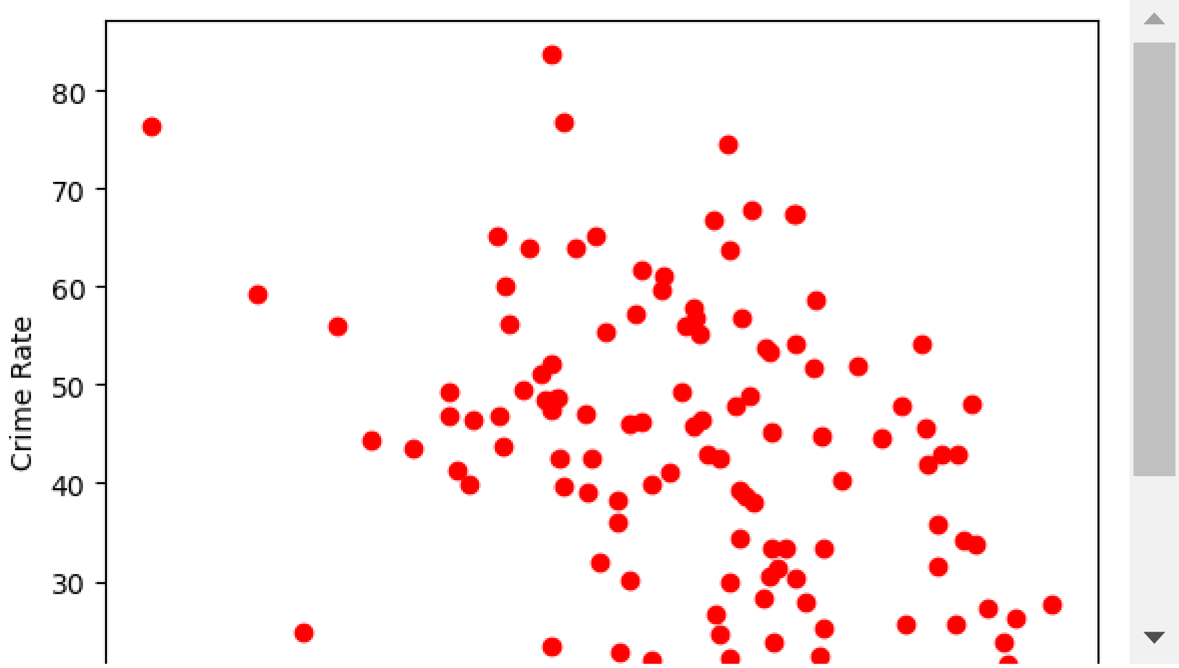
In [34]:
```
plt.scatter(x = df['Gini Coefficient'], y = df['Crime Rate'], c='r')
plt.xlabel("Literacy Rate")
plt.ylabel("Crime Rate")
plt.show()
```



In [35]:
```
plt.scatter(x = df['Literacy Rate'], y = df['Crime Rate'], c='r')
plt.xlabel("Literacy Rate")
plt.ylabel("Crime Rate")
plt.show()
```



In [36]:
```
plt.scatter(x = df['Happiness Index'], y = df['Crime Rate'], c='r')
plt.xlabel("Happiness Index")
plt.ylabel("Crime Rate")
plt.show()
```



In [37]:
```
print(f"The data has dimensions {df.shape[0]} by {df.shape[1]}")
```

```
The data has dimensions 114 by 10
```

Models

Linear Regression

In [38]:
```
x = df['Unemployment (%)']
y = df['Crime Rate']
```

In [39]:
```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size = 0.2, rand
```

In [40]:
```
print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(91,)
(23,)
(91,)
(23,)
```

In [41]:
```
x_train = x_train.values.reshape(-1,1)
x_test = x_test.values.reshape(-1,1)
```

In [42]:
```
model = LinearRegression()
```

In [43]:
```
model.fit(x_train,y_train)
```

Out[43]:
```
LinearRegression()
```

In [44]:
```
model.score(x_test,y_test)
```

Out[44]:
```
-0.007634769384835982
```

In [45]:
```
model.coef_
```

Out[45]:
```
array([0.02319364])
```

In [46]:
```
model.intercept_
```

Out[46]:
```
43.92981780961712
```

In [47]:
```
model.predict(x_test)
```

Out[47]:
```
array([44.04346663, 44.09449263, 44.12696373, 44.31019346, 44.224377  ,
       44.15943482, 43.97388572, 44.36121946, 44.05506345, 43.95301145,
       44.01795363, 44.7485532 , 44.19654464, 44.30555473, 44.19422527,
       44.045786  , 43.97620508, 44.05506345, 44.09217327, 44.096812  ,
       44.05274409, 44.08985391, 44.01099554])
```

SVR

In [48]:
```
svr_reg = SVR(kernel='rbf')
```

In [49]:
```
svr_reg.fit(x_train, y_train)
```

Out[49]:
```
SVR()
```

In [50]:
```
svr_reg.score(x_test, y_test)
```

Out[50]:
```
-0.0130052739576616
```

In [51]:
```
svr_reg.predict(x_test)
```

Out[51]:
```
array([44.46390688, 43.1346723 , 42.74214205, 42.46102554, 42.57927347,
       42.65155736, 46.33796802, 43.18547422, 44.10723728, 46.58850538,
       45.2636075 , 45.04111084, 42.64761599, 42.43307761, 42.6498702 ,
       44.39131868, 46.29854224, 44.10723728, 43.17759932, 43.09377038,
       44.17709812, 43.22253485, 45.47010505])
```

Random Forest

In [52]:
```
forest_reg = RandomForestRegressor(n_estimators=100)
```

In [53]:
```
forest_reg.fit(x_train, y_train)
```

Out[53]:
```
RandomForestRegressor()
```

In [54]:
```
forest_reg.score(x_test, y_test)
```

Out[54]:
```
-0.18084155194459428
```

In [55]:
```
forest_reg.predict(x_test)
```

Out[55]:
```
array([44.38873056, 47.9662    , 34.19316   , 42.05879333, 39.19645   ,
       41.00206667, 50.13535024, 38.1855    , 45.63565   , 47.3021    ,
       46.21371667, 50.3416    , 47.08810333, 44.00199333, 47.08810333,
       53.02751889, 47.39150857, 45.63565   , 56.49124   , 34.3573    ,
       48.90143333, 37.78749   , 57.45489333])
```

1

Linear Regression

In [56]:
```
x1 = df['HDI']
y1 = df['Crime Rate']
```

In [57]:
```
x1_train, x1_test, y1_train, y1_test = train_test_split(x1,y1,test_size=0.2,r
```

In [58]:
```
print(x1_train.shape)
print(x1_test.shape)
print(y1_train.shape)
print(y1_test.shape)
```

```
(91,)
(23,)
(91,)
(23,)
```

In [59]:
```
x1_train = x1_train.values.reshape(-1,1)
x1_test = x1_test.values.reshape(-1,1)
```

In [60]:
```
model1 = LinearRegression()
```

In [61]:
```
model1.fit(x1_train,y1_train)
```

Out[61]:
```
LinearRegression()
```

In [62]:
```
model1.score(x1_test,y1_test)
```

Out[62]:
```
0.32143810677152107
```

In [63]:
```
model1.coef_
```

Out[63]:
```
array([-63.99590998])
```

In [64]:
```
model1.intercept_
```

Out[64]:
```
94.03296273541734
```

In [65]:
```
model1.predict(x1_test)
```

Out[65]:
```
array([35.15672555, 47.95590755, 38.35652105, 44.11615295, 49.87578485,
       44.11615295, 44.11615295, 47.95590755, 33.23684825, 51.79566215,
       44.11615295, 48.59586665, 46.03603025, 46.67598935, 56.91533494,
       40.91635745, 60.11513044, 44.11615295, 38.99648015, 33.23684825,
       34.51676645, 34.51676645, 32.59688915])
```

SVR

In [66]:
```
svr_reg1 = SVR(kernel='rbf')
```

In [67]:
```
svr_reg1.fit(x1_train, y1_train)
```

Out[67]:
```
SVR()
```

In [68]:
```
svr_reg1.score(x1_test, y1_test)
```

Out[68]:
```
0.3127046067027307
```

In [69]:
```
svr_reg1.predict(x1_test)
```

Out[69]:
```
array([34.23008381, 47.57808431, 35.98305197, 44.11910437, 48.1916991 ,
       44.11910437, 44.11910437, 47.57808431, 34.79484483, 48.32911347,
       44.11910437, 47.85188657, 46.25008374, 46.78225915, 47.93194721,
       39.40017803, 47.4137718 , 44.11910437, 36.71618651, 34.79484483,
       34.29533805, 34.29533805, 35.19957637])
```

Random Forest

In [70]:
```
forest_reg1 = RandomForestRegressor(n_estimators=100)
```

In [71]:
```
forest_reg1.fit(x1_train, y1_train)
```

Out[71]:
```
RandomForestRegressor()
```

In [72]:
```
forest_reg1.score(x1_test, y1_test)
```

Out[72]:
```
0.3452532418140508
```

In [73]:
```
forest_reg1.predict(x1_test)
```

Out[73]:
```
array([28.19300896, 44.7477156 , 31.25552738, 38.50618694, 52.970615  ,
       38.50618694, 38.50618694, 44.7477156 , 35.2240506 , 51.84502833,
       38.50618694, 62.00152583, 48.25800643, 52.15575714, 49.664675  ,
       35.29104758, 48.72078389, 38.50618694, 34.59829381, 35.2240506 ,
       43.46410524, 43.46410524, 35.63863119])
```

2

Linear Regression

In [74]:
```
x2 = df['Population Density (per sq. km)']
y2 = df['Crime Rate']
```

In [75]:
```
x2_train, x2_test, y2_train, y2_test = train_test_split(x2,y2,test_size=0.2,r
```

In [76]:
```
print(x2_train.shape)
print(x2_test.shape)
print(y2_train.shape)
print(y2_test.shape)
```

```
(91,)
(23,)
(91,)
(23,)
```

In [77]:
```
x2_train = x2_train.values.reshape(-1,1)
x2_test = x2_test.values.reshape(-1,1)
```

In [78]:
```
model2 = LinearRegression()
```

In [79]:
```
model2.fit(x2_train,y2_train)
```

Out[79]:
```
LinearRegression()
```

In [80]:
```
model2.score(x2_test,y2_test)
```

Out[80]:
```
-0.005095386322439888
```

In [81]:
```
model2.coef_
```

Out[81]:
```
array([-0.00251465])
```

In [82]:
```
model2.intercept_
```

Out[82]:
```
44.94808952748543
```

In [83]:
```
model2.predict(x2_test)
```

Out[83]:
```
array([44.69159477, 44.5960379 , 44.87264989, 44.88522317, 44.74440251,
       44.76451975, 44.60861117, 44.93803091, 44.36217503, 44.55077412,
       44.78715164, 44.82990077, 44.90282575, 44.76954906, 44.89025247,
       44.93048695, 44.79972491, 44.13334147, 44.66896288, 44.94054556,
       44.90282575, 44.93803091, 44.90785506])
```

SVR

In [84]:
```
svr_reg2 = SVR(kernel='rbf')
```

In [85]:
```
svr_reg2.fit(x2_train, y2_train)
```

Out[85]:
```
SVR()
```

In [86]:
```
svr_reg2.score(x2_test, y2_test)
```

Out[86]:
```
-0.00013250373905360213
```

In [87]:
```
svr_reg2.predict(x2_test)
```

Out[87]:
```
array([45.15593899, 45.07773789, 45.29843327, 45.307964  , 45.19839552,
       45.21439539, 45.08811036, 45.34737195, 44.88271286, 45.04023721,
       45.23226875, 45.26563408, 45.3212137 , 45.21837911, 45.31176087,
       45.34180602, 45.24213743, 44.6945231 , 45.13756166, 45.34922237,
       45.3212137 , 45.34737195, 45.32497884])
```

Random Forest

In [88]:
```
forest_reg2 = RandomForestRegressor(n_estimators=100)
```

In [89]:
```
forest_reg2.fit(x2_train, y2_train)
```

Out[89]:
```
RandomForestRegressor()
```

In [90]:
```
forest_reg2.score(x2_test, y2_test)
```

Out[90]:
```
-0.01640067852072602
```

In [91]:
```
forest_reg2.predict(x2_test)
```

Out[91]:
```
array([39.52772738, 26.3438    , 40.49636083, 58.15442   , 40.2067    ,
       30.68758833, 26.9288    , 53.04505333, 39.3867    , 35.9838    ,
       41.70095   , 53.82524167, 45.57842   , 39.19027167, 52.08337   ,
       46.55233   , 50.32431   , 33.4489    , 32.03393333, 53.04505333,
       45.57842   , 53.04505333, 37.05922833])
```

3

Linear Regression

In [92]:
```
x3 = df['Weapons per 100 persons']
y3 = df['Crime Rate']
```

In [93]:
```
x3_train, x3_test, y3_train, y3_test = train_test_split(x3,y3,test_size=0.2,r
```

In [94]:
```
print(x3_train.shape)
print(x3_test.shape)
print(y3_train.shape)
print(y3_test.shape)
```

```
(91,)
(23,)
(91,)
(23,)
```

In [95]:
```
x3_train = x3_train.values.reshape(-1,1)
x3_test = x3_test.values.reshape(-1,1)
```

In [96]:
```
model3 = LinearRegression()
```

In [97]:
```
model3.fit(x3_train,y3_train)
```

Out[97]:
```
LinearRegression()
```

In [98]:
```
model3.score(x3_test,y3_test)
```

Out[98]:
```
0.011175677484889457
```

In [99]:
```
model3.coef_
```

Out[99]:
```
array([-0.0514453])
```

In [100]:
```
model3.intercept_
```

Out[100]:
```
44.74899843687709
```

In [101]:
```
model3.predict(x3_test)
```

Out[101]:
```
array([43.94645174, 44.74899844, 44.20882278, 44.64610784, 44.50206099,
       44.23968996, 43.97217439, 44.06477594, 43.74067054, 44.1265103 ,
       44.08535406, 44.24997902, 44.64096331, 44.69240861, 44.70269767,
       44.60495159, 44.7078422 , 44.62552971, 44.41460398, 43.1181824 ,
       43.39598702, 42.9638465 , 43.26737377])
```

SVR

In [102]:
```
svr_reg3 = SVR(kernel='rbf')
```

In [103]:
```
svr_reg3.fit(x3_train, y3_train)
```

Out[103]:
```
SVR()
```

In [104]:
```
svr_reg3.score(x3_test, y3_test)
```

Out[104]:
```
0.10048243215727704
```

In [105]:
```
svr_reg3.predict(x3_test)
```

Out[105]:
```
array([44.14316076, 46.15945938, 45.3836997 , 46.24589361, 46.18384984,
       45.50493833, 44.27533258, 44.73799666, 43.08044816, 45.02870683,
       44.83683512, 45.54372369, 46.2475019 , 46.2194387 , 46.21071938,
       46.25103422, 46.20598554, 46.2506833 , 46.03520341, 40.98775912,
       41.58914448, 40.95896123, 41.22694699])
```

Random Forest

In [106]:
```
forest_reg3 = RandomForestRegressor(n_estimators=100)
```

In [107]:
```
forest_reg3.fit(x3_train, y3_train)
```

Out[107]:
```
RandomForestRegressor()
```

In [108]:
```
forest_reg3.score(x3_test, y3_test)
```

Out[108]:
```
-0.6611520413716885
```

In [109]:
```
forest_reg3.predict(x3_test)
```

Out[109]:
```
array([58.7413    , 28.089425  , 37.824025  , 58.15426667, 34.382     ,
       35.32251667, 60.6626    , 32.2933    , 48.64389   , 53.79801   ,
       48.35365   , 35.54521667, 60.97126667, 53.48525833, 53.29064   ,
       52.46877   , 53.29064   , 45.59397571, 38.6878    , 42.5926    ,
       28.5001    , 43.9949    , 37.6976    ])
```

4

Linear Regression

In [110]:
```
x4 = df['Per Capita Income']
y4 = df['Crime Rate']
```

In [111]:
```
x4_train, x4_test, y4_train, y4_test = train_test_split(x4,y4,test_size=0.2,r
```

In [112]:
```
print(x4_train.shape)
print(x4_test.shape)
print(y4_train.shape)
print(y4_test.shape)
```

```
(91,)
(23,)
(91,)
(23,)
```

In [113]:
```
x4_train = x4_train.values.reshape(-1,1)
x4_test = x4_test.values.reshape(-1,1)
```

In [114]:
```
model4 = LinearRegression()
```

In [115]:
```
model4.fit(x4_train,y4_train)
```

Out[115]:
```
LinearRegression()
```

In [116]:
```
model4.score(x4_test,y4_test)
```

Out[116]:
```
0.3153957542949096
```

In [117]:
```
model4.coef_
```

Out[117]:
```
array([-0.00027998])
```

In [118]:
```
model4.intercept_
```

Out[118]:
```
49.1055243486027
```

In [119]:
```
model4.predict(x4_test)
```

Out[119]:
```
array([41.88857751, 48.02201641, 44.10206945, 47.38003095, 48.23535828,
       48.10964896, 47.09277536, 47.91758528, 36.2520964 , 47.8926674 ,
       46.7744424 , 47.67932552, 48.16256446, 48.17656327, 48.82974778,
       46.55466108, 48.79335087, 48.05057398, 43.71206259, 31.28671827,
       36.79441033, 36.90976053, 30.38323503])
```

SVR

In [120]:
```
svr_reg4 = SVR(kernel='rbf')
```

In [121]:
```
svr_reg4.fit(x4_train, y4_train)
```

Out[121]:
```
SVR()
```

In [122]:
```
svr_reg4.score(x4_test, y4_test)
```
Out[122]:
```
0.28090009868366994
```

In [123]:
```
svr_reg4.predict(x4_test)
```
Out[123]:
```
array([35.85091264, 46.61052663, 39.89481009, 45.94106534, 46.77775343,
       46.68263052, 45.56495234, 46.51843352, 33.8265832 , 46.49547476,
       45.09759201, 46.28356272, 46.72386823, 46.73448688, 47.09362575,
       44.74634918, 47.08064274, 46.63454435, 39.09175899, 36.81532655,
       33.61639667, 33.57837264, 37.32828955])
```

Random Forest

In [124]:
```
forest_reg4 = RandomForestRegressor(n_estimators=100)
```

In [125]:
```
forest_reg4.fit(x4_train, y4_train)
```
Out[125]:
```
RandomForestRegressor()
```

In [126]:
```
forest_reg4.score(x4_test, y4_test)
```
Out[126]:
```
-0.3994050497065751
```

In [127]:
```
forest_reg4.predict(x4_test)
```
Out[127]:
```
array([31.5444, 59.3112, 41.0899, 46.6959, 53.3791, 59.8615, 59.595 ,
       36.7283, 28.1862, 39.9704, 55.2157, 45.9484, 47.9635, 47.5894,
       52.4315, 46.8404, 39.9893, 76.5287, 31.6221, 40.4215, 36.8379,
       36.8379, 40.4215])
```

5

Linear Regression

In [128]:
```
x5 = df['Gini Coefficient']
y5 = df['Crime Rate']
```

In [129]:
```
x5_train, x5_test, y5_train, y5_test = train_test_split(x5,y5,test_size=0.2,r
```

In [130]:
```
print(x5_train.shape)
print(x5_test.shape)
print(y5_train.shape)
print(y5_test.shape)
```

```
(91,)
(23,)
(91,)
(23,)
```

In [131]:
```
x5_train = x5_train.values.reshape(-1,1)
x5_test = x5_test.values.reshape(-1,1)
```

In [132]:
```
model5 = LinearRegression()
```

In [133]:
```
model5.fit(x5_train,y5_train)
```

Out[133]:
```
LinearRegression()
```

In [134]:
```
model5.score(x5_test,y5_test)
```

Out[134]:
```
0.4530645360329869
```

In [135]:
```
model5.coef_
```

Out[135]:
```
array([0.62063201])
```

In [136]:
```
model5.intercept_
```

Out[136]:
```
21.211269769609814
```

In [137]:
```
model5.predict(x5_test)
```

Out[137]:
```
array([36.2305644 , 45.41591813, 43.3057693 , 47.77431977, 45.72623414,
       37.40976521, 43.80227491, 64.22106802, 41.00943087, 51.18779582,
       49.38796299, 60.31108636, 38.34071323, 41.56799968, 56.6493575 ,
       38.27865003, 46.34686615, 45.91242374, 36.85119641, 37.84420762,
       41.38181007, 42.18863169, 37.96833402])
```

SVR

In [138]:
```
svr_reg5 = SVR(kernel='rbf')
```

In [139]:
```
svr_reg5.fit(x5_train, y5_train)
```

Out[139]:
```
SVR()
```

In [140]:
```
svr_reg5.score(x5_test, y5_test)
```

Out[140]:
```
0.2008518024611211
```

In [141]:
```
svr_reg5.predict(x5_test)
```

Out[141]:
```
array([45.89564691, 45.77020051, 43.28107089, 49.2475491 , 46.23177636,
       44.99652934, 43.72687361, 48.9795316 , 42.65225759, 51.76912538,
       50.96163082, 49.42310439, 44.23403081, 42.5907365 , 50.29389484,
       44.28452963, 47.17708882, 46.51355887, 45.43895478, 44.64108119,
       42.59703536, 42.67910806, 44.5389364 ])
```

Random Forest

In [142]:
```
forest_reg5 = RandomForestRegressor(n_estimators=100)
```

In [143]:
```
forest_reg5.fit(x5_train, y5_train)
```

Out[143]:
```
RandomForestRegressor()
```

In [144]:
```
forest_reg5.score(x5_test, y5_test)
```

Out[144]:
```
0.3588368129241213
```

In [145]:
```
forest_reg5.predict(x5_test)
```

Out[145]:
```
array([35.05723333, 39.89549   , 44.7086    , 55.9291    , 35.854275  ,
       43.49393333, 30.2801    , 53.5648    , 44.79775   , 54.1714    ,
       57.50536   , 59.4784    , 59.14012667, 40.67691667, 54.8984    ,
       39.92108833, 43.38316667, 35.50665667, 48.34063333, 34.37767   ,
       26.95124167, 33.8825    , 34.05347   ])
```

6

Linear Regression

In [146]:
```
x6 = df['Literacy Rate']
y6 = df['Crime Rate']
```

In [147]:
```
x6_train, x6_test, y6_train, y6_test = train_test_split(x6,y6,test_size=0.2,r
```

In [148]:
```
print(x6_train.shape)
print(x6_test.shape)
print(y6_train.shape)
print(y6_test.shape)
```

```
(91,)
(23,)
(91,)
(23,)
```

In [149]:
```
x6_train = x6_train.values.reshape(-1,1)
x6_test = x6_test.values.reshape(-1,1)
```

In [150]:
```
model6 = LinearRegression()
```

In [151]:
```
model6.fit(x6_train,y6_train)
```

Out[151]:
```
LinearRegression()
```

In [152]:
```
model6.score(x6_test,y6_test)
```

Out[152]:
```
0.04319159714172249
```

In [153]:
```
model6.coef_
```

Out[153]:
```
array([-34.45618803])
```

In [154]:
```
model6.intercept_
```

Out[154]:
```
74.95362857734011
```

In [155]:
```
model6.predict(x6_test)
```

Out[155]:
```
array([40.49744055, 42.56481183, 40.49744055, 42.22024995, 49.45604944,
       40.49744055, 41.53112619, 43.59849747, 40.84200243, 47.73324004,
       42.56481183, 42.56481183, 47.38867815, 46.69955439, 53.24623012,
       40.49744055, 47.38867815, 42.90937371, 40.49744055, 40.84200243,
       40.84200243, 40.84200243, 40.84200243])
```

SVR

In [156]:
```
svr_reg6 = SVR(kernel='rbf')
```

In [157]:
```
svr_reg6.fit(x6_train, y6_train)
```

Out[157]:
```
SVR()
```

In [158]:
```
svr_reg6.score(x6_test, y6_test)
```

Out[158]:
```
0.167615464513455
```

In [159]:
```
svr_reg6.predict(x6_test)
```

Out[159]:
```
array([40.84631457, 44.53683658, 40.84631457, 43.78676105, 50.5587106 ,
       40.84631457, 42.40412438, 46.81952691, 41.2802156 , 51.18262257,
       44.53683658, 44.53683658, 51.18904877, 51.0267064 , 48.64329591,
       40.84631457, 51.18904877, 45.30356173, 40.84631457, 41.2802156 ,
       41.2802156 , 41.2802156 , 41.2802156 ])
```

Random Forest

In [160]:
```
forest_reg6 = RandomForestRegressor(n_estimators=100)
```

In [161]:
```
forest_reg6.fit(x6_train, y6_train)
```

Out[161]:
```
RandomForestRegressor()
```

In [162]:
```
forest_reg6.score(x6_test, y6_test)
```

Out[162]:
```
-0.19039503863544294
```

In [163]:
```
forest_reg6.predict(x6_test)
```

Out[163]:
```
array([36.70503748, 33.20642723, 36.70503748, 48.07715818, 43.22954167,
       36.70503748, 37.31651916, 54.891555  , 35.17039062, 55.2653    ,
       33.20642723, 33.20642723, 57.20365   , 60.34185   , 45.4062    ,
       36.70503748, 57.20365   , 59.90141976, 36.70503748, 35.17039062,
       35.17039062, 35.17039062, 35.17039062])
```

7

Linear Regression

In [164]:
```
x7 = df['Happiness Index']
y7 = df['Crime Rate']
```

In [165]:
```
x7_train, x7_test, y7_train, y7_test = train_test_split(x7,y7,test_size=0.2,r
```

In [166]:
```
print(x7_train.shape)
print(x7_test.shape)
print(y7_train.shape)
print(y7_test.shape)
```

```
(91,)
(23,)
(91,)
(23,)
```

In [167]:
```
x7_train = x7_train.values.reshape(-1,1)
x7_test = x7_test.values.reshape(-1,1)
```

In [168]:
```
model7 = LinearRegression()
```

In [169]:
```
model7.fit(x7_train,y7_train)
```

Out[169]:
```
LinearRegression()
```

In [170]:
```
model7.score(x7_test,y7_test)
```

Out[170]:
```
0.16410372862277356
```

In [171]:
```
model7.coef_
```

Out[171]:
```
array([-5.12646703])
```

In [172]:
```
model7.intercept_
```

Out[172]:
```
73.52237520652292
```

In [173]:
```
model7.predict(x7_test)
```

Out[173]:
```
array([40.40539817, 46.09577658, 42.60977899, 43.58380773, 48.3001574 ,
       48.50521608, 42.81483767, 45.78818855, 36.81687124, 40.50792751,
       41.12310355, 48.09509872, 48.45395141, 49.94062685, 52.65765438,
       41.99460295, 54.96456454, 51.32477295, 41.07183888, 34.8175491 ,
       36.2016952 , 37.12445927, 35.63778383])
```

SVR

In [174]:
```
svr_reg7 = SVR(kernel='rbf')
```

In [175]:
```
svr_reg7.fit(x7_train, y7_train)
```

Out[175]:
```
SVR()
```

In [176]:
```
svr_reg7.score(x7_test, y7_test)
```

Out[176]:
```
0.12153635315848066
```

In [177]:
```
svr_reg7.predict(x7_test)
```

Out[177]:
```
array([43.34250604, 46.25396994, 44.34833436, 44.86317948, 47.16200822,
       47.20802026, 44.45347727, 46.08999993, 41.82092284, 43.3851016 ,
       43.64712273, 47.10757259, 47.19733564, 47.25960698, 46.16714444,
       44.04504053, 45.15250608, 46.84693609, 43.62477838, 41.16943637,
       41.5701516 , 41.95389023, 41.37176619])
```

Random Forest

In [178]:
```
forest_reg7 = RandomForestRegressor(n_estimators=100)
```

In [179]:
```
forest_reg7.fit(x7_train, y7_train)
```

Out[179]:
```
RandomForestRegressor()
```

In [180]:
```
forest_reg7.score(x7_test, y7_test)
```

Out[180]:
```
-0.6553073368071656
```

In [181]:
```
forest_reg7.predict(x7_test)
```

Out[181]:
```
array([40.661835  , 37.634     , 55.6608    , 30.22006667, 42.65736667,
       52.50917667, 38.80165   , 47.45156   , 36.5825    , 47.75648333,
       63.1008    , 41.29906667, 52.50917667, 57.2738    , 47.74817095,
       32.71185   , 33.9463    , 47.61097095, 63.0869    , 24.3231    ,
       29.5589    , 46.7577    , 41.0305    ])
```

In [182]:
```
df
```

Out[182]:

	Country	Crime Rate	Unemployment (%)	HDI	Population Density (per sq. km)	Weapons per 100 persons	Per Capita Income	Gini Coefficient	Li
0	Afghanistan	76.31	11.2	0.51	57.0	12.5	508.0	27.8	
1	Albania	42.53	11.3	0.80	100.0	12.0	5181.0	33.2	
2	Algeria	52.03	11.5	0.75	18.0	2.1	3368.0	27.6	
3	Argentina	63.82	7.0	0.85	16.0	7.4	8476.0	41.4	
4	Armenia	22.79	7.7	0.78	99.0	6.1	4266.0	34.4	
...	...	...	...	...	...	...	...	...	
109	Uzbekistan	33.42	8.9	0.72	73.0	0.4	1724.0	39.7	
110	Venezuela	83.76	9.4	0.71	32.0	18.5	3740.0	46.9	
111	Vietnam	46.19	8.8	0.70	289.0	1.6	2786.0	35.7	

Multi Linear Regression

In [183]:
```
xm1 = df[['HDI','Per Capita Income','Gini Coefficient']]
ym1 = df['Crime Rate']
```

In [184]:
```
xm1
```

Out[184]:

	HDI	Per Capita Income	Gini Coefficient
0	0.51	508.0	27.8
1	0.80	5181.0	33.2
2	0.75	3368.0	27.6
3	0.85	8476.0	41.4
4	0.78	4266.0	34.4
...	...	...	...
109	0.72	1724.0	39.7
110	0.71	3740.0	46.9
111	0.70	2786.0	35.7
112	0.58	985.0	57.1
113	0.57	1466.0	44.3

114 rows × 3 columns

In [185]:
```
ym1
```

Out[185]:
```
0      76.31
1      42.53
2      52.03
3      63.82
4      22.79
       ...
109    33.42
110    83.76
111    46.19
112    43.62
113    59.30
Name: Crime Rate, Length: 114, dtype: float64
```

In [186]:
```
xm1_train, xm1_test, ym1_train, ym1_test = train_test_split(xm1,ym1,test_size
```

In [187]:
```
print(xm1_train.shape)
print(xm1_test.shape)
print(ym1_train.shape)
print(ym1_test.shape)
```

```
(91, 3)
(23, 3)
(91,)
(23,)
```

In [188]:
```
modelm1 = LinearRegression()
```

In [189]:
```
modelm1.fit(xm1_train,ym1_train)
```

Out[189]:
```
LinearRegression()
```

In [190]:
```
modelm1.score(xm1_test,ym1_test)
```

Out[190]:
```
0.48113848194465014
```

In [191]:
```
modelm1.coef_
```

Out[191]:
```
array([-5.23222342e+01, -2.33629887e-05,  3.48531555e-01])
```

In [192]:
```
modelm1.intercept_
```

Out[192]:
```
72.48753222576923
```

In [193]:
```
modelm1.predict(xm1_test)
```

Out[193]:
```
array([32.18331266, 48.31783951, 38.95739189, 46.44935404, 50.07957491,
       40.68976101, 44.19478166, 58.86963124, 32.82699493, 54.68772333,
       47.30500194, 57.17722288, 42.78664098, 45.12339556, 62.01877567,
       38.43183544, 58.84622637, 45.45971373, 35.82334142, 30.63514139,
       34.12781265, 34.59052923, 30.10623299])
```

SVR

In [194]:
```
svr_regm1 = SVR(kernel='rbf')
```

In [195]:
```
svr_regm1.fit(xm1_train, ym1_train)
```

Out[195]:
```
SVR()
```

In [196]:
```
svr_regm1.score(xm1_test, ym1_test)
```

Out[196]:
```
0.26912304434070666
```

In [197]:
```
svr_regm1.predict(xm1_test)
```

Out[197]:
```
array([37.54415613, 46.6103703 , 41.09669345, 46.0088298 , 46.77337422,
       46.67960435, 45.68855913, 46.52373865, 34.46078224, 46.50240448,
       45.29966594, 46.30954469, 46.71987568, 46.73033788, 47.12632391,
       45.01174941, 47.10903443, 46.63328372, 40.42876815, 36.98823361,
       34.36363646, 34.35139456, 37.49824151])
```

Random Forest

In [198]:
```
forest_regm1 = RandomForestRegressor(n_estimators=100)
```

In [199]:
```
forest_regm1.fit(xm1_train, ym1_train)
```

Out[199]:
```
RandomForestRegressor()
```

In [200]:
```
forest_regm1.score(xm1_test, ym1_test)
```

Out[200]:
```
0.615189731813497
```

In [201]:
```
forest_regm1.predict(xm1_test)
```

Out[201]:
```
array([29.8903, 49.9496, 38.5791, 54.8225, 53.4245, 37.152 , 41.1599,
       63.7695, 36.5538, 69.121 , 56.6845, 65.6901, 48.6371, 45.5487,
       61.3467, 43.3275, 51.9259, 37.3772, 30.3314, 35.4381, 28.708 ,
       34.6374, 34.3302])
```