In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df=pd.read_csv(r"C:\Users\Admin\Downloads\2015 - 2015.csv")
df
```

Out[2]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Fre
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	0.6
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0.6
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0.6
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0.6
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0.6
...	...	...	...	...	...	...	...	...	
153	Rwanda	Sub-Saharan Africa	154	3.465	0.03464	0.22208	0.77370	0.42864	0.5
154	Benin	Sub-Saharan Africa	155	3.340	0.03656	0.28665	0.35386	0.31910	0.4
155	Syria	Middle East and Northern Africa	156	3.006	0.05015	0.66320	0.47489	0.72193	0.1
156	Burundi	Sub-Saharan Africa	157	2.905	0.08658	0.01530	0.41587	0.22396	0.1
157	Togo	Sub-Saharan Africa	158	2.839	0.06727	0.20868	0.13995	0.28443	0.3

158 rows × 12 columns

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 158 entries, 0 to 157
Data columns (total 12 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Country                        158 non-null    object 
 1   Region                         158 non-null    object 
 2   Happiness Rank                 158 non-null    int64  
 3   Happiness Score                158 non-null    float64
 4   Standard Error                 158 non-null    float64
 5   Economy (GDP per Capita)       158 non-null    float64
 6   Family                         158 non-null    float64
 7   Health (Life Expectancy)       158 non-null    float64
 8   Freedom                        158 non-null    float64
 9   Trust (Government Corruption)  158 non-null    float64
 10  Generosity                     158 non-null    float64
 11  Dystopia Residual              158 non-null    float64
dtypes: float64(9), int64(1), object(2)
memory usage: 14.9+ KB
```

In [4]:

```
df.columns
```

Out[4]:

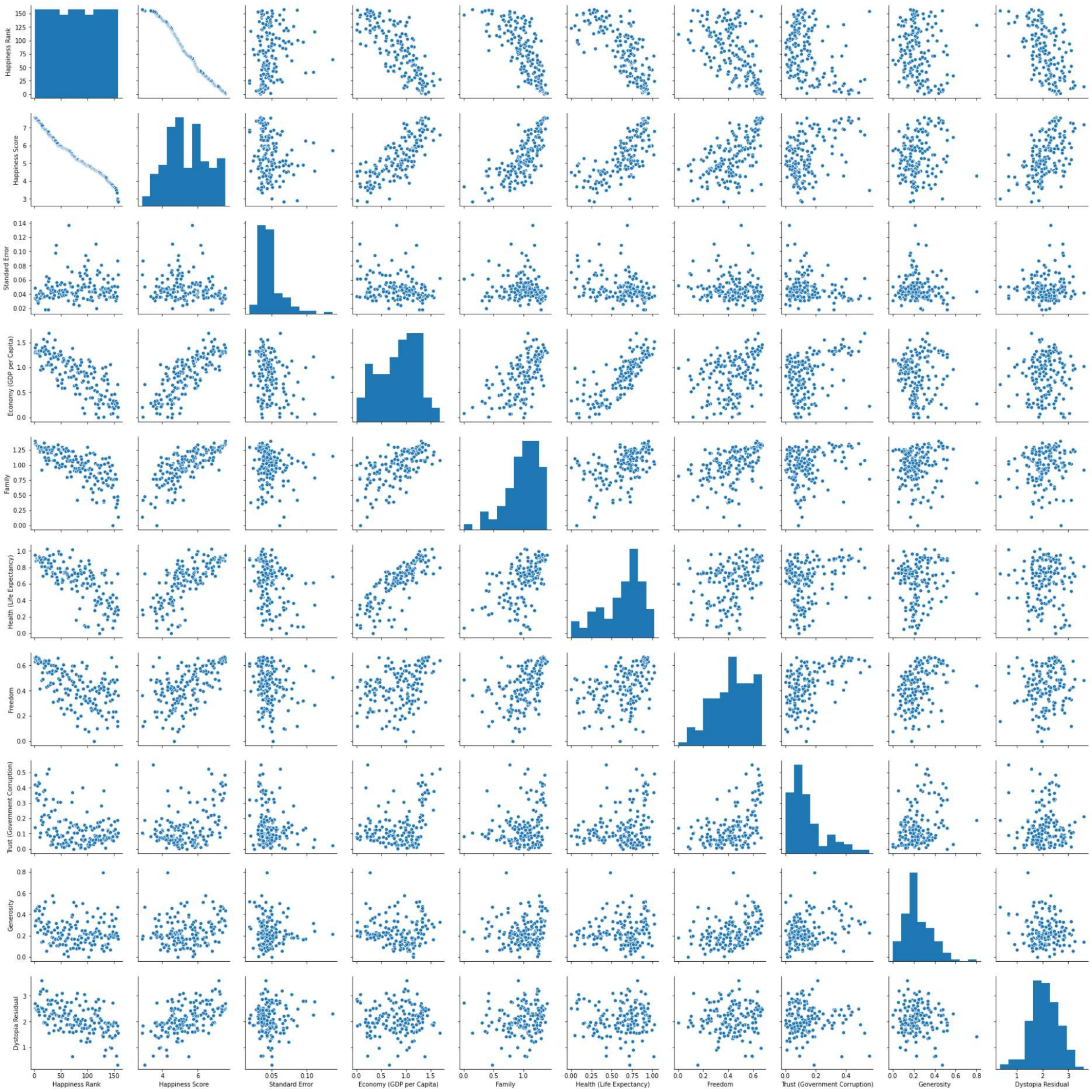
```
Index(['Country', 'Region', 'Happiness Rank', 'Happiness Score',
       'Standard Error', 'Economy (GDP per Capita)', 'Family',
       'Health (Life Expectancy)', 'Freedom', 'Trust (Government Corruptio
n)',
       'Generosity', 'Dystopia Residual'],
      dtype='object')
```

In [5]:

```
sns.pairplot(df)
```

Out[5]:

```
<seaborn.axisgrid.PairGrid at 0x1fbb03c54f0>
```

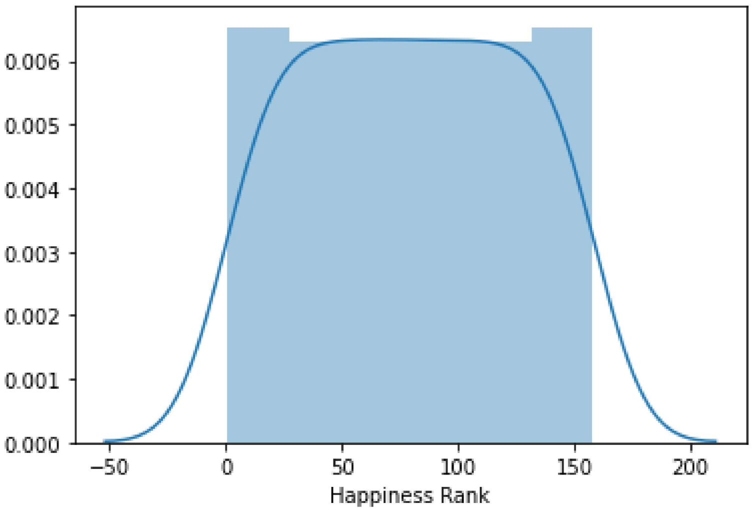


In [6]:

```
sns.distplot(df['Happiness Rank'])
```

Out[6]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fbb3c3d100>
```

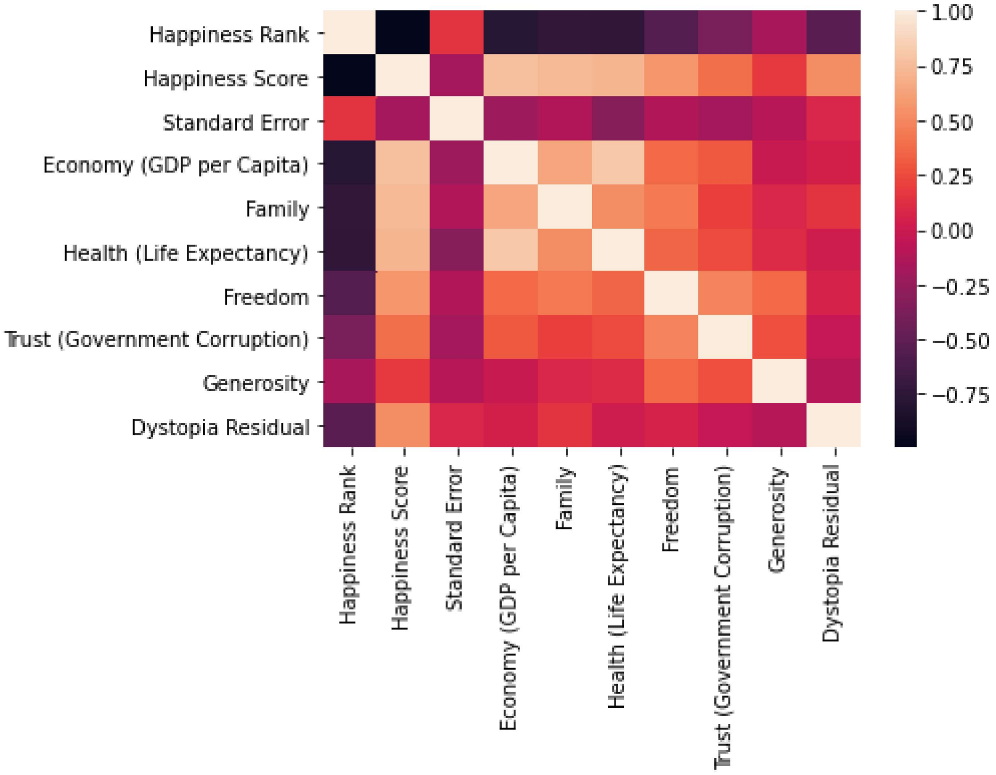


In [7]:

```
sns.heatmap(df.corr())
```

Out[7]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1fbb4bf0e50>
```



In [8]:

```
x=df[['Happiness Score', 'Family']]
y=df[['Happiness Rank']]
```

In [9]:

```
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 [10]:
```
from sklearn.linear_model import LinearRegression
lr= LinearRegression()
lr.fit(x_train,y_train)
```

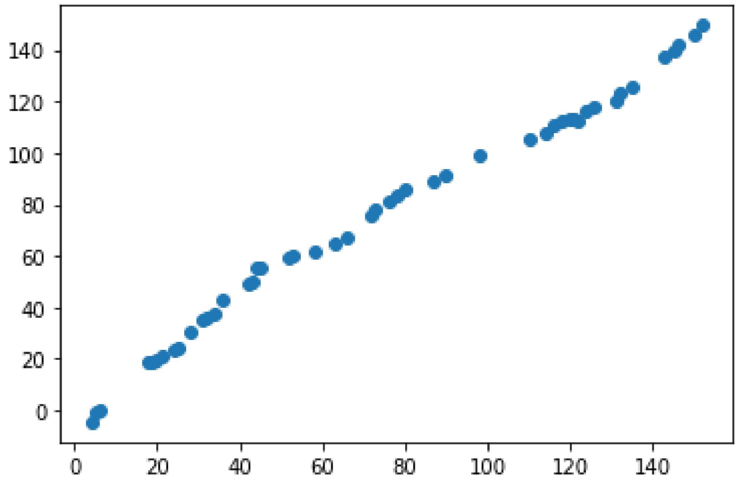
Out[10]:
```
LinearRegression()
```

In [11]:
```
print(lr.intercept_)
```

```
[288.9286642]
```

In [12]:
```
prediction= lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[12]:
```
<matplotlib.collections.PathCollection at 0x1fbb56dcd00>
```



In [13]:
```
print(lr.score(x_test,y_test))
```

```
0.9834201132826216
```

In [14]:
```
print(lr.score(x_train,y_train))
```

```
0.9840515520087789
```

In [15]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [16]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```

Out[16]:
```
Ridge(alpha=10)
```

In [17]:
```
rr.score(x_test,y_test)
```

Out[17]:
```
0.9748133747211096
```

In [18]:
```
la=Lasso(alpha=10)
la.fit(x_train,y_train)
```

Out[18]:
```
Lasso(alpha=10)
```

In [19]:
```
la.score(x_test,y_test)
```

Out[19]:
```
0.9315097457666321
```

In [20]:
```
from sklearn.linear_model import ElasticNet
en=ElasticNet()
en.fit(x_train,y_train)
```

Out[20]:
```
ElasticNet()
```

In [21]:
```
print(en.intercept_)
```

```
[231.81415025]
```

In [22]:
```
print(en.predict(x_test))
```

```
[ 61.73048977  35.28094626 101.45396566  37.23148303  67.51096886
  22.59757367  70.73055952 102.54665831  65.57035927 102.77106793
  84.54064552 129.71785956  88.0301143  104.07675815 129.2003886
  19.34914565  45.40784629  92.73048896 120.99447294  37.59769936
  81.19718533  52.35122725  59.00788467  35.66424621  22.00213807
  49.04692469  58.88088405  47.87644393  61.25709471 109.05696192
  77.50946431 100.47473259  76.87536753  83.11487927 103.50386608
  64.83636601 123.82065534 105.06553154  40.14602704  40.4545485
  86.74101749  48.41982068 124.11680746 111.83090435  68.92747968
 110.23231929 113.33361192 106.21400485]
```

In [23]:
```
print(en.score(x_test,y_test))
```

```
0.8886190207984758
```

Evaluation

In [24]:
```
from sklearn import metrics
```

In [25]:
```
print("Mean Absolute Error",metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error 5.10029717045476
```

In [26]:
```
print("Mean Squared Error",metrics.mean_squared_error(y_test,prediction))
```

```
Mean Squared Error 35.05529201134163
```

```
In [27]: print("Root Mean Squared Error:",np.sqrt(metrics.mean_squared_error(y_test,pred
```

```
Root Mean Squared Error: 5.920750966840409
```

```
In [ ]:
```