Problem Statement:

Context:

The World Happiness Report is a landmark survey of the state of global happiness. The first report was published in 2012, the second in 2013, the third in 2015, and the fourth in the 2016 Update. The World Happiness 2017, which ranks 155 countries by their happiness levels, was released at the United Nations at an event celebrating International Day of Happiness on March 20th. The report continues to gain global recognition as governments, organizations and civil society increasingly use happiness indicators to inform their policy-making decisions. Leading experts across fields – economics, psychology, survey analysis, national statistics, health, public policy and more – describe how measurements of well-being can be used effectively to assess the progress of nations. The reports review the state of happiness in the world today and show how the new science of happiness explains personal and national variations in happiness.
The happiness scores and rankings use data from the Gallup World Poll. The scores are based on answers to the main life evaluation question asked in the poll. This question, known as the Cantril ladder, asks respondents to think of a ladder with the best possible life for them being a 10 and the worst possible life being a 0 and to rate their own current lives on that scale. The scores are from nationally representative samples for the years 2013-2016 and use the Gallup weights to make the estimates representative. The columns following the happiness score estimate the extent to which each of six factors – economic production, social support, life expectancy, freedom, absence of corruption, and generosity – contribute to making life evaluations higher in each country than they are in Dystopia, a hypothetical country that has values equal to the world's lowest national averages for each of the six factors. They have no impact on the total score reported for each country, but they do explain why some countries rank higher than others.

Importing requried libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import pickle
import plotly
import plotly.graph_objects as go
import chart_studio.plotly as py
from plotly.offline import iplot
import seaborn as sns
from scipy.stats import zscore
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression, LogisticRegression, LassoCV, L
from sklearn.preprocessing import power_transform, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import r2_score, mean_squared_error
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Reading Data

In [2]:
```
df = pd.read_csv(r"C:\Users\Kushal Arya\Desktop\Data Analysis With Python\ML File
df.head()
```

Out[2]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	0.6655
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0.6287
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0.6493
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0.6697
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0.6329

In [3]:
```
# Here we use shape command to know total no of rows and columns present in our d

print('Rows and Columns in Dataset : ', df.shape )
```

```
Rows and Columns in Dataset :  (158, 12)
```

In [4]:

```python
# Here we use info command to know all details about dataset i.e, size, type etc.
print('-----------------------------------------------------------------------------
print('\nInformations of dataset :-\n')
print(df.info())
print('\n---------------------------------------------------------------------------
```

```
-----------------------------------------------------------------------------

Informations of dataset :-

<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
None

-----------------------------------------------------------------------------
```

In [5]:
```python
# Here we use isna() command to identify of nan in our dataset.
print('-----------------------------------------------------------------------------
print('\nNaN in dataset :-\n')
print(df.isna().sum())
print('\n-------------------------------------------------------------------------
```

```
---------------------------------------------------------------------------

NaN in dataset :-

Country                          0
Region                           0
Happiness Rank                   0
Happiness Score                  0
Standard Error                   0
Economy (GDP per Capita)         0
Family                           0
Health (Life Expectancy)         0
Freedom                          0
Trust (Government Corruption)    0
Generosity                       0
Dystopia Residual                0
dtype: int64

---------------------------------------------------------------------------
```

There is no null values in dataset.

Statistic of Dataset

In [6]:
```python
# We use describe command to extracte statistical infomation about dataset.
df.describe()
```

Out[6]:

	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	(Gov Cor
count	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	158
mean	79.493671	5.375734	0.047885	0.846137	0.991046	0.630259	0.428615	C
std	45.754363	1.145010	0.017146	0.403121	0.272369	0.247078	0.150693	C
min	1.000000	2.839000	0.018480	0.000000	0.000000	0.000000	0.000000	C
25%	40.250000	4.526000	0.037268	0.545808	0.856823	0.439185	0.328330	C
50%	79.500000	5.232500	0.043940	0.910245	1.029510	0.696705	0.435515	C
75%	118.750000	6.243750	0.052300	1.158448	1.214405	0.811013	0.549092	C
max	158.000000	7.587000	0.136930	1.690420	1.402230	1.025250	0.669730	C

In [7]:
```
# Display maximum rows.
pd.set_option("display.max_rows", None)
```

In [8]:
```
# Here we group region and country by their Happiness Rank .
group = df.groupby(['Region','Country'])[[ 'Happiness Rank', 'Happiness Score', '
group
```

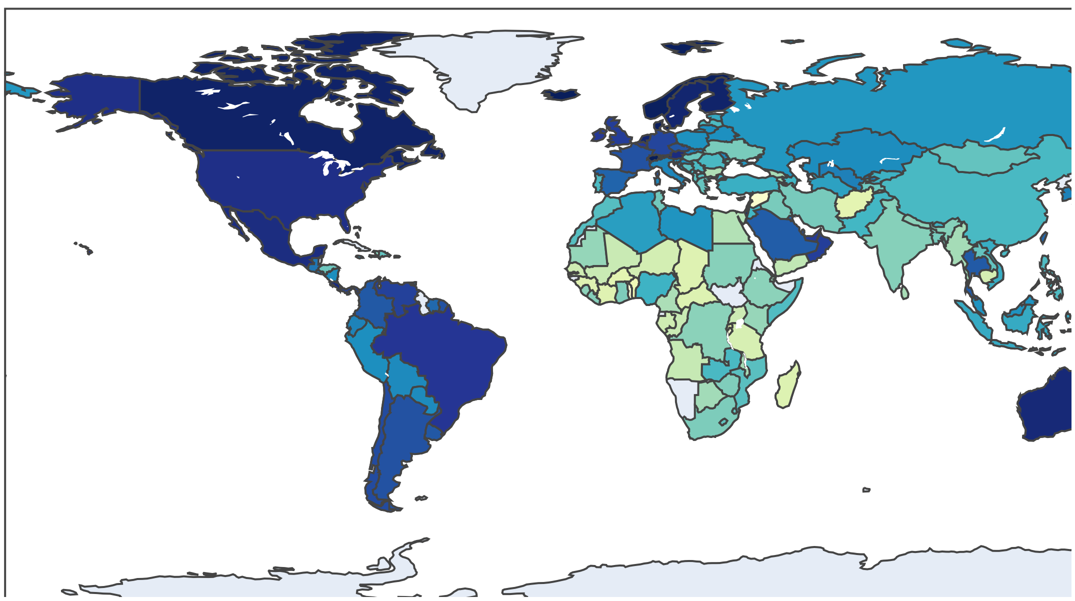
Australia and New Zealand	**Australia**	10	7.284	1.33358	0.93156
	New Zealand	9	7.286	1.25018	0.90837
Central and Eastern Europe	**Albania**	95	4.959	0.87867	0.81325
	Armenia	127	4.350	0.76821	0.72990
	Azerbaijan	80	5.212	1.02389	0.64045
	Belarus	59	5.813	1.03192	0.73608
	Bosnia and Herzegovina	96	4.949	0.83223	0.79081
	Bulgaria	134	4.218	1.01216	0.76649
	Croatia	62	5.759	1.08254	0.78805
	Czech Republic	31	6.505	1.17898	0.84483
	Estonia	73	5.429	1.15174	0.77361
	Georgia	130	4.297	0.74190	0.72926

Australia and New Zealand are most happiest region.

Map representation of Countries Happiness Score.

In [9]:
```
data = dict(type = 'choropleth',
           locations = df['Country'],
           locationmode = 'country names',
           z = df['Happiness Score'],
           text = df['Country'],
           colorscale = 'YlGnBu',
           autocolorscale = False,
          )
layout = dict(geo = {'scope':'world'})

diagram = go.Figure(data = [data], layout = layout)
iplot(diagram)
```



Drop unwanted column

In [10]:
```
df = df.drop(columns =['Region','Country'], axis = 1)
df.head()
```

Out[10]:

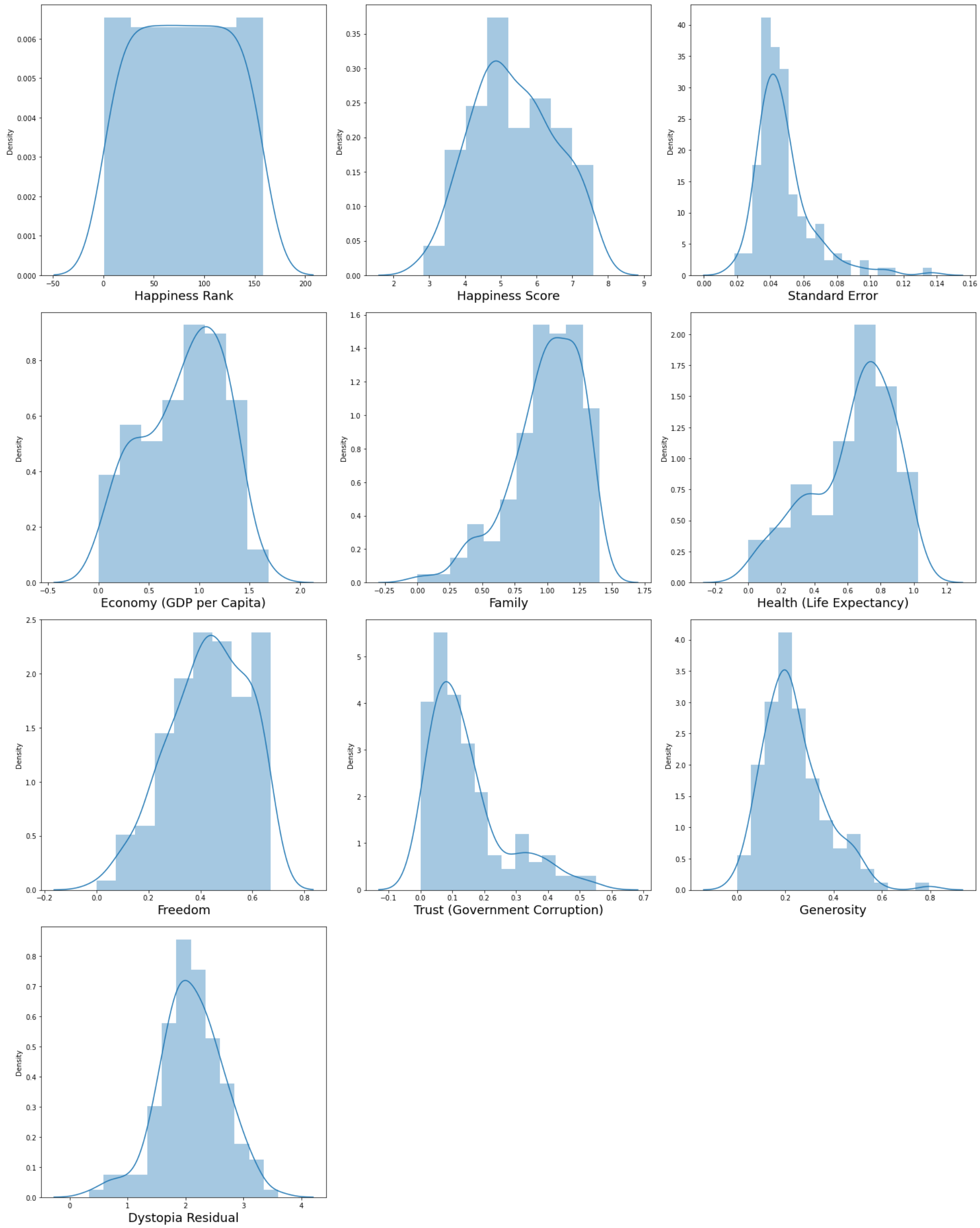
	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)	Gene
0	1	7.587	0.03411	1.39651	1.34951	0.94143	0.66557	0.41978	0.
1	2	7.561	0.04884	1.30232	1.40223	0.94784	0.62877	0.14145	0.
2	3	7.527	0.03328	1.32548	1.36058	0.87464	0.64938	0.48357	0.
3	4	7.522	0.03880	1.45900	1.33095	0.88521	0.66973	0.36503	0.
4	5	7.427	0.03553	1.32629	1.32261	0.90563	0.63297	0.32957	0

We drop column because we want to visualizing data how it's distributed.

In [11]:
```python
# Let' see how data is distributed in every columns.
print('\nDistribution Plot :-\n')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in df:
    if plotnumber <=12:
        ax = plt.subplot(4,3, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
Distribution Plot :-
```



Here we found outlier in some columns.

Visualizing relationship

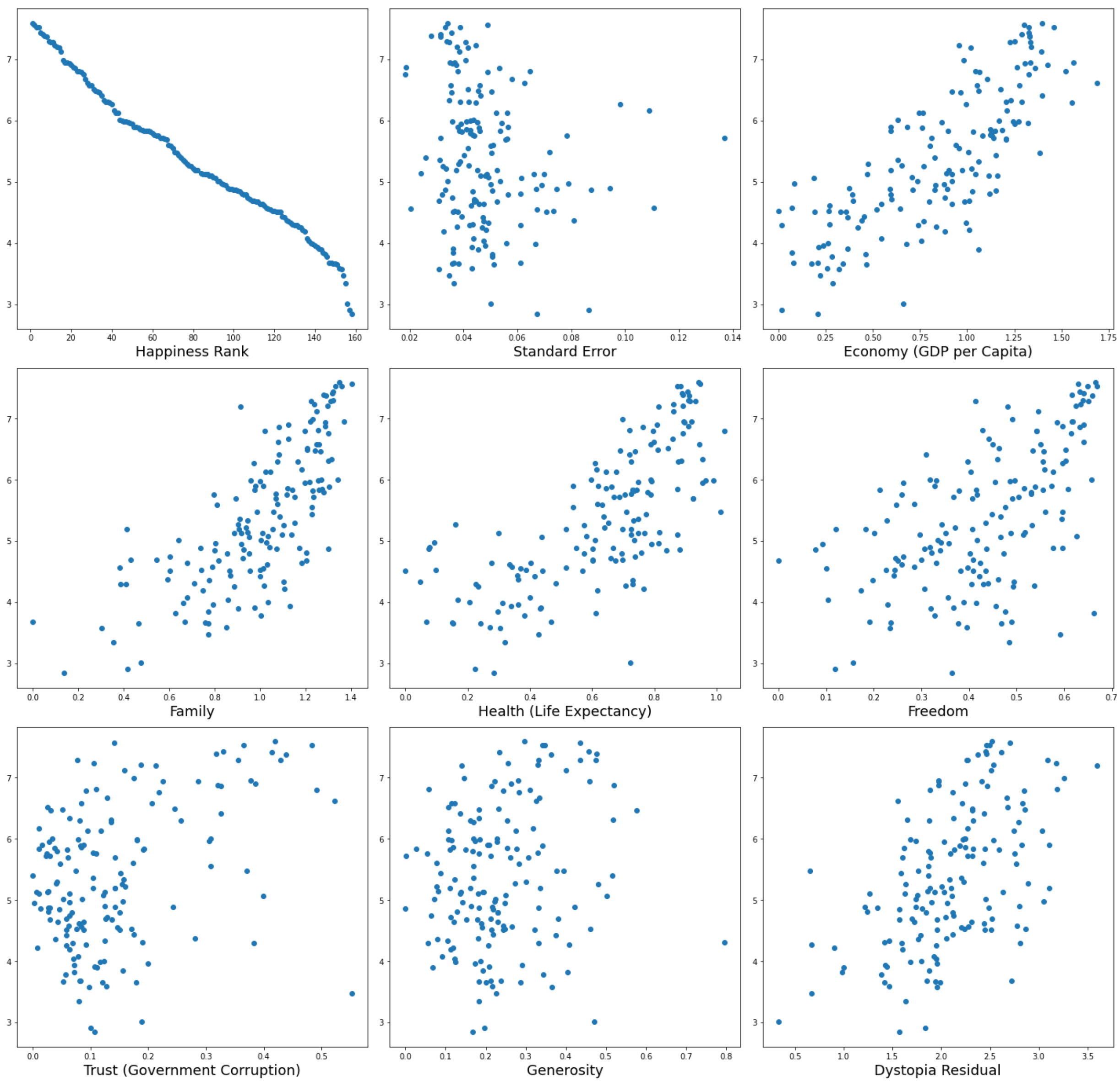
In [12]:
```
# Before visulalizing we have to devide dataset into feature and label.
x = df.drop('Happiness Score', axis = 1)
y = df['Happiness Score']
```

In [13]:

```python
# Let' see how data is related to label .
print('\nRelationship Plot :-\n')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in x:
    if plotnumber <=12:
        ax = plt.subplot(4,3, plotnumber)
        plt.scatter(x[column], y)
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

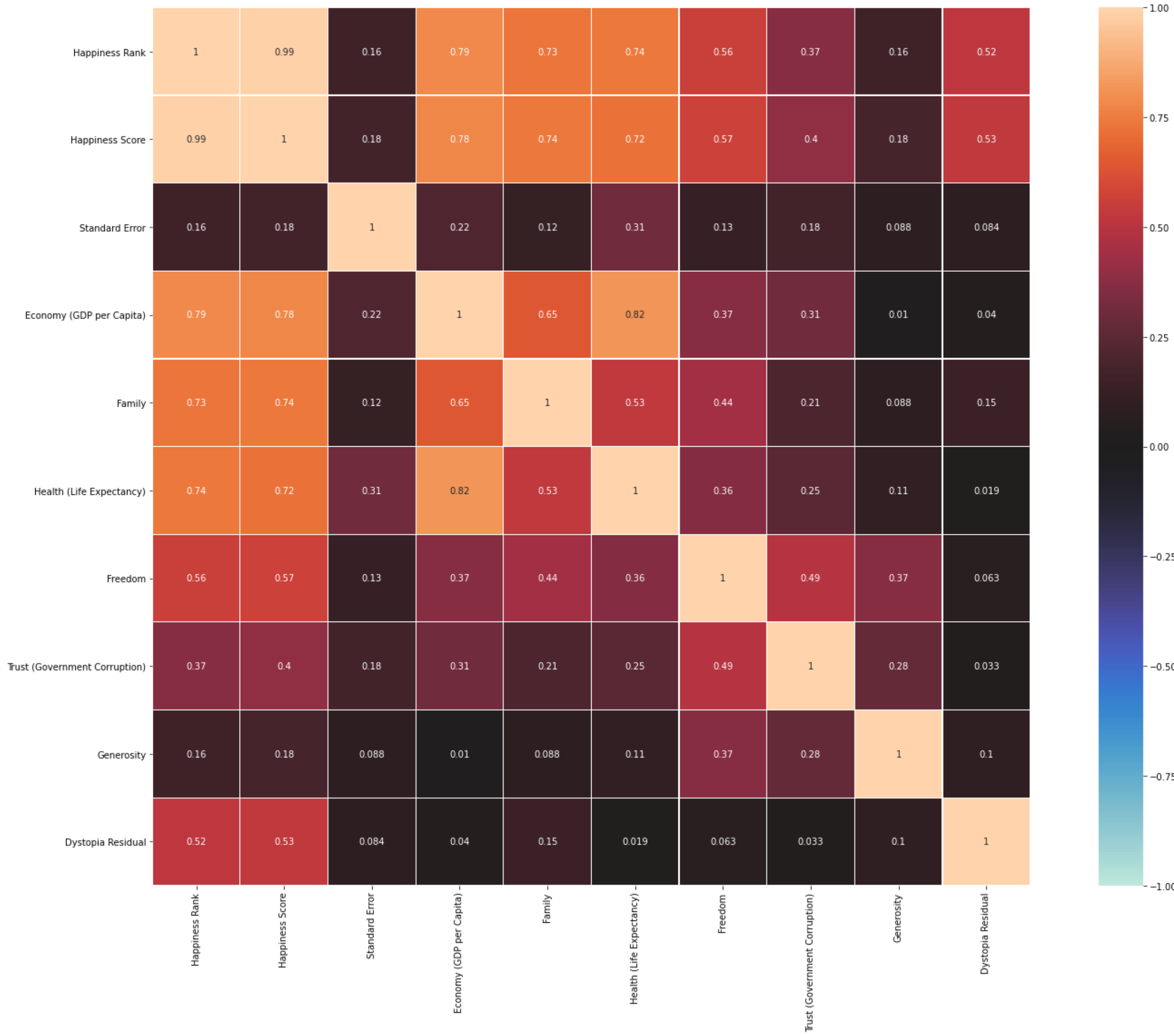
```
Relationship Plot :-
```



Plotting Heatmap (Correlation matrix)

In [14]:
```
df_corr = df.corr().abs()

plt.figure(figsize = (22,16))
sns.heatmap(df_corr, vmin = -1, annot = True, square = True, center = 0, fmt = '.
plt.tight_layout()
```

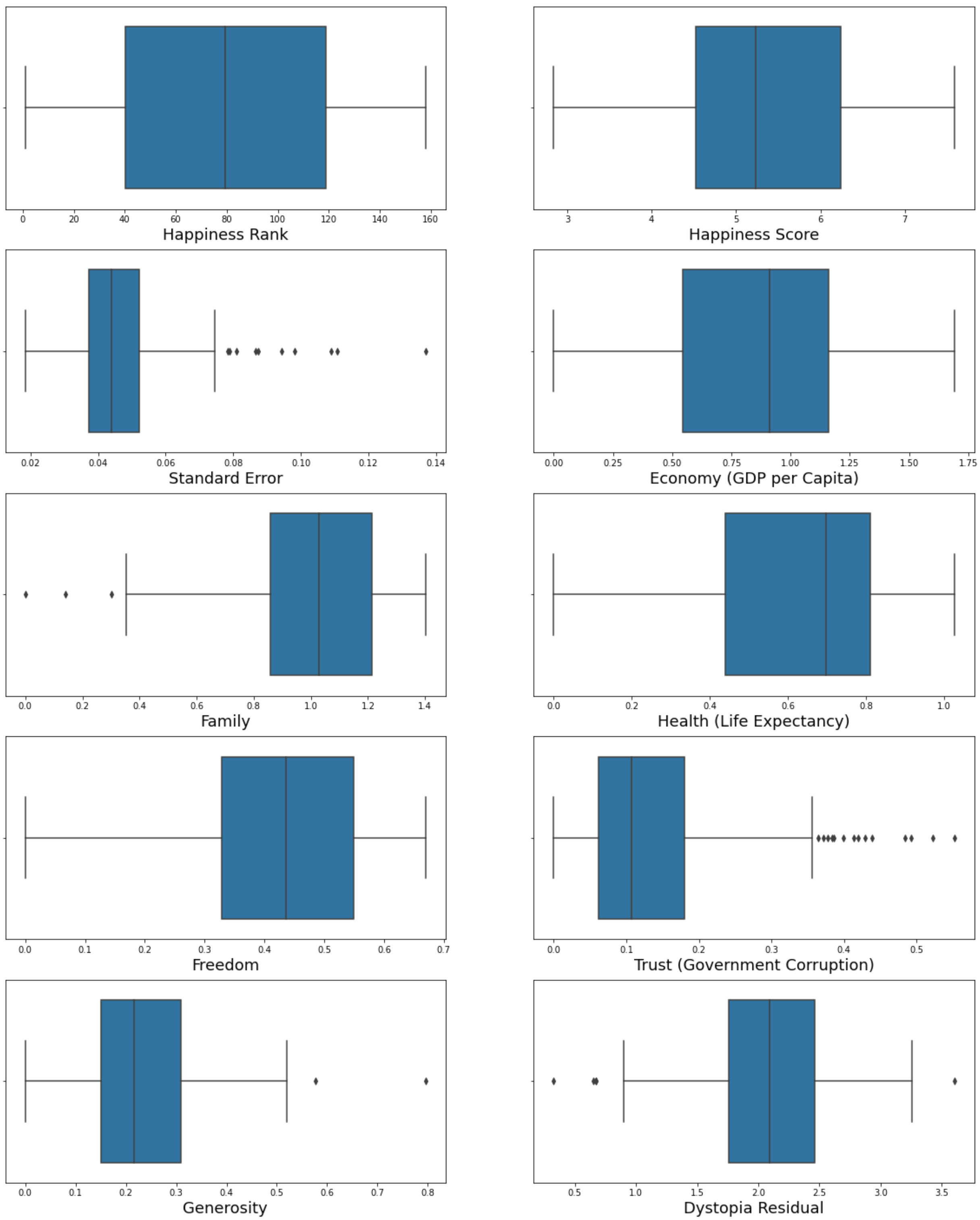


Observation : Happiness Score and Happiness Rank are corelated .

Detecting Outlier with the help of boxplot

In [15]:
```python
# Visualize the outliers using boxplot
plt.figure(figsize = (20,30))
graph = 1

for column in df:
    if graph <=12:
        ax = plt.subplot(6,2, graph)
        sns.boxplot(df[column], orient = 'v')
        plt.xlabel(column, fontsize = 18)
    graph +=1
plt.show()
```



Outlier present in our dataset.

Removing Outlier

In [16]:
```
# we are removing the top 2% data from the Dystopia Residual column
q = df['Dystopia Residual'].quantile(0.98)
data_cleaned = df[df['Dystopia Residual']<q]
# we are removing the top 1% data from the Generosity column
q = df['Generosity'].quantile(0.99)
data_cleaned = data_cleaned[data_cleaned['Generosity']<q]
# we are removing the top 5% data from the Trust (Government Corruption) column
q = df['Trust (Government Corruption)'].quantile(0.90)
data_cleaned = data_cleaned[data_cleaned['Trust (Government Corruption)']<q]
# we are removing the top 5% data from the Standard Error  column
q = df['Standard Error'].quantile(0.95)
data_cleaned = data_cleaned[data_cleaned['Standard Error']<q]
# we are removing the top 5% data from the Health (Life Expectancy)  column
q = df['Health (Life Expectancy)'].quantile(0.95)
data_cleaned = data_cleaned[data_cleaned['Health (Life Expectancy)']<q]
```

In [17]:
```
df.shape
```

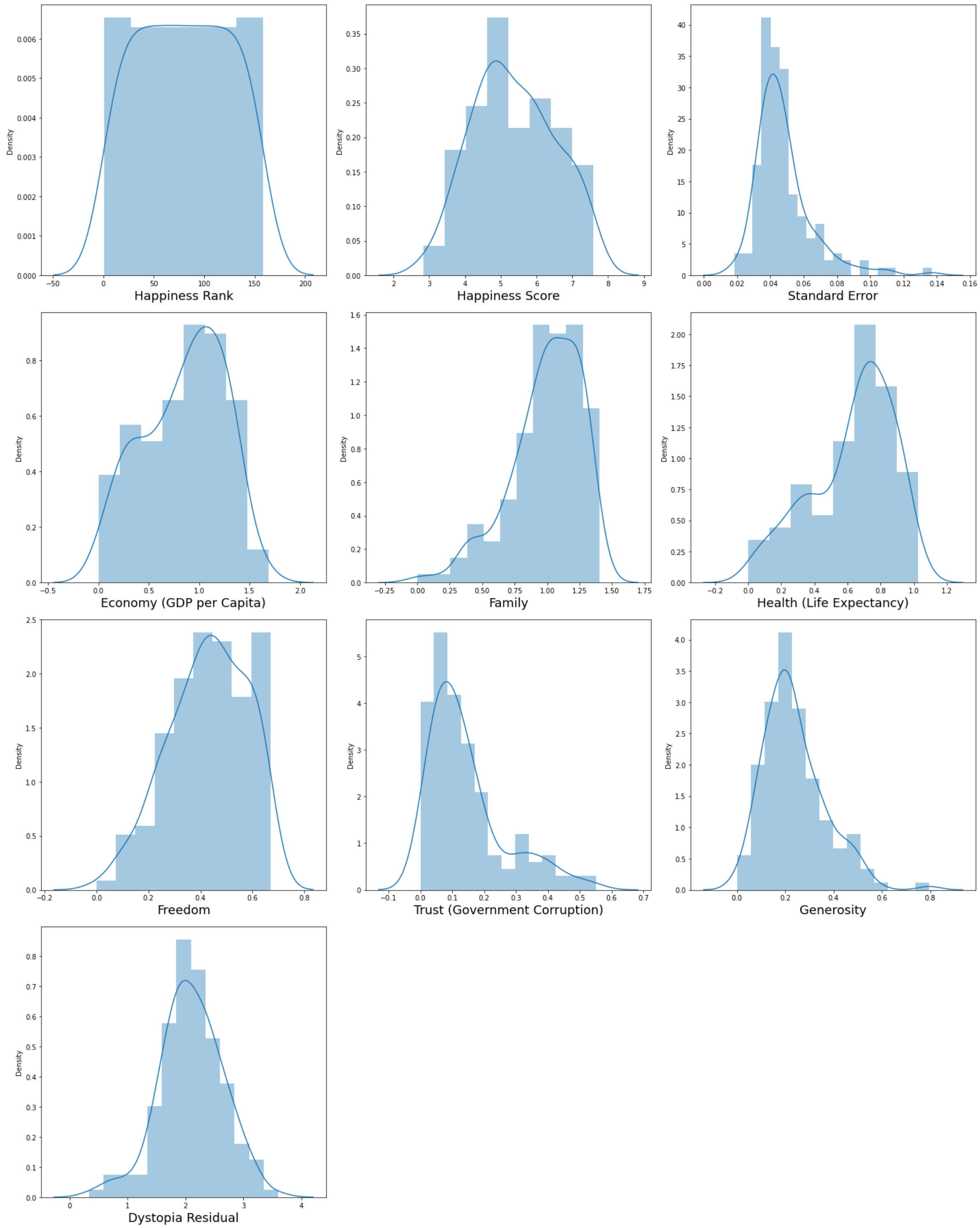
Out[17]:
```
(158, 10)
```

In [18]:

```
# Let' see outliers are removed in columns or not.
print('\nDistribution Plot :-\n')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in df:
    if plotnumber <=12:
        ax = plt.subplot(4,3, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
Distribution Plot :-
```



Outliers are removed from our dataset.

Checking skewness present in our dataset.

In [19]:
```
df.skew()
```

Out[19]:
```
Happiness Rank                   0.000418
Happiness Score                  0.097769
Standard Error                   1.983439
Economy (GDP per Capita)        -0.317575
Family                          -1.006893
Health (Life Expectancy)        -0.705328
Freedom                         -0.413462
Trust (Government Corruption)    1.385463
Generosity                       1.001961
Dystopia Residual               -0.238911
dtype: float64
```

Skewness present in our dataset.

Removing skewness using Power Transform .

In [20]:
```
df1 = power_transform(x)
df1 = pd.DataFrame(df1, columns = x.columns)
```

In [21]:
```
# Checking skewness
df1.skew()
```

Out[21]:
```
Happiness Rank                  -0.264365
Standard Error                  -0.020092
Economy (GDP per Capita)        -0.127233
Family                          -0.169651
Health (Life Expectancy)        -0.183181
Freedom                         -0.080728
Trust (Government Corruption)    0.185965
Generosity                       0.013320
Dystopia Residual                0.022925
dtype: float64
```

In [22]:
```
df1.head() # seeing our data set
```

Out[22]:

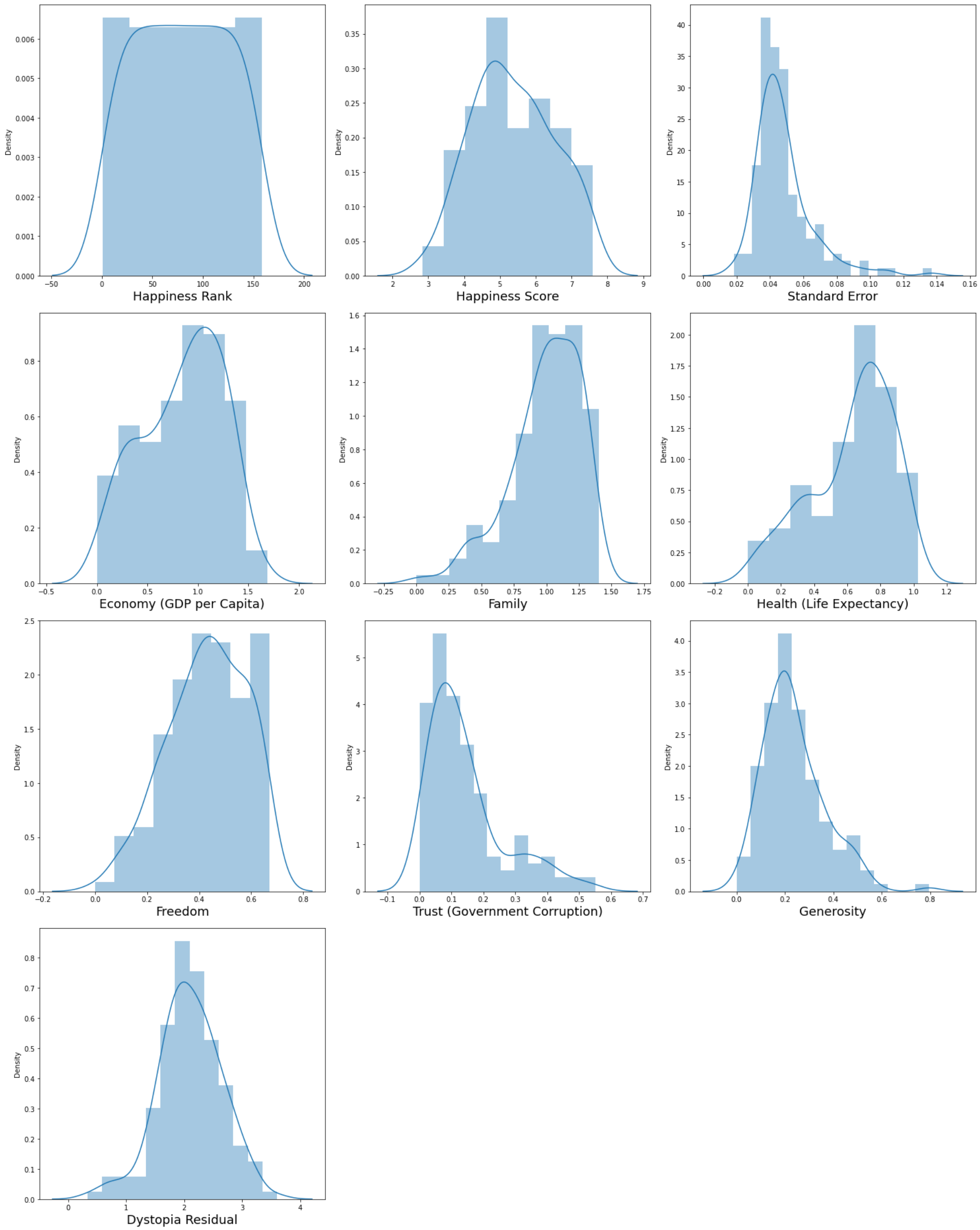
	Happiness Rank	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	Trust (Government Corruption)	Generosity	Dy Re
0	-2.063414	-0.972226	1.446061	1.669206	1.491765	1.756335	1.773991	0.622391	0.7
1	-2.008498	0.309350	1.173321	2.012132	1.532348	1.439946	0.315993	1.480995	1.1
2	-1.958574	-1.062017	1.239836	1.739586	1.085223	1.615733	1.906792	0.927973	0.7
3	-1.912062	-0.503610	1.630246	1.553118	1.147600	1.792821	1.624007	0.964080	0.6
4	-1.868100	-0.823548	1.242168	1.501726	1.270179	1.475479	1.503484	1.592224	0.6

In [23]:

```
# Let' check skewness are removed in columns or not.
print('\nDistribution Plot :-\n')

plt.figure(figsize = (20,25), facecolor = 'white')
plotnumber = 1
for column in df:
    if plotnumber <=12:
        ax = plt.subplot(4,3, plotnumber)
        sns.distplot(df[column])
        plt.xlabel(column, fontsize = 18)
    plotnumber += 1
plt.tight_layout()
```

```
Distribution Plot :-
```



Skewness removed from our dataset.

Checking Multicollinearity present in our dataset we use VIF.

In [24]:
```
vif = pd.DataFrame()
vif['Features'] = x.columns
vif['Vif'] = [variance_inflation_factor(df1.values,i) for i in range(df1.shape[1]
vif
```

Out[24]:

	Features	Vif
0	Happiness Rank	83.686479
1	Standard Error	1.145322
2	Economy (GDP per Capita)	14.093148
3	Family	6.705455
4	Health (Life Expectancy)	8.585592
5	Freedom	3.459032
6	Trust (Government Corruption)	2.086227
7	Generosity	2.064874
8	Dystopia Residual	18.293069

Obsevation : Multicollinearity present our dataset. Our dataset is small if we remove we lost some important value and we did not build good model to order to avoid this problem we deside to go with multicollinearity.

Data Scaling

In [25]:
```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
x_scaled
```

Out[25]:
```
array([[-1.72099989, -0.80592569,  1.36962124, ...,  2.30965159,
         0.47103971,  0.75825809],
       [-1.69907456,  0.05588945,  1.13522625, ..., -0.01647953,
         1.57585637,  1.09285682],
       [-1.67714922, -0.8544869 ,  1.19286069, ...,  2.8427738 ,
         0.8242928 ,  0.71233526],
       ...,
       [ 1.67742676,  0.13253425, -0.45524543, ...,  0.38141902,
         1.85689094, -3.20843049],
       [ 1.69935209,  2.26396166, -2.06756644, ..., -0.35771452,
        -0.31694987, -0.48198451],
       [ 1.72127743,  1.13418227, -1.58633379, ..., -0.30180313,
        -0.5581534 , -0.96361241]])
```

We scaled our features data above.

Split data into train and test. Model will be bulit on training data and

tested on test data.

In [26]:
```
x_train, x_test, y_train, y_test = train_test_split(x_scaled, y, test_size = 0.25
print('Data has been splited.')
```

```
Data has been splited.
```

Model Building.

Linear Regression model instantiaing, training and evaluating

In [27]:
```
Lr = LinearRegression()
Lr.fit(x_train, y_train)
y_pred = Lr.predict(x_test)
```

In [28]:
```
print('Score of test data ---->', Lr.score(x_test, y_test))
```

```
Score of test data ----> 0.9999999533878745
```

In [29]:
```
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
```

```
MSE of Model -------> 6.832299011078998e-08
```

In [30]:
```
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
```

```
RMSE of Model -------> 0.00026138666781377773
```

Here we use Lasso Regularization to avoid overfitting

In [31]:
```
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[31]:
```
LassoCV(normalize=True)
```

In [32]:
```
alpha = lassocv.alpha_
alpha
```

Out[32]:
```
0.00010200443251839897
```

In [33]:
```
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[33]:
```
Lasso(alpha=0.00010200443251839897)
```

In [34]:
```python
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9999992584089135
```

Conclusion : Linear Regression model has 99% score and there is no overfitting.

Knn model instantiaing, training and evaluating

In [35]:
```python
Knn = KNeighborsRegressor()
Knn.fit(x_train, y_train)
y_pred = Knn.predict(x_test)
```

In [36]:
```python
print('----------------------------------------------------------\n')
print('Score of test data ---->', Knn.score(x_test, y_test))
print('\n---------------------------------------------------------\n')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('\n---------------------------------------------------------\n')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('\n---------------------------------------------------------')
print('\n R2 Score ----->', r2_score(y_test, y_pred))
print('\n------------------------------------------------------------')
```

```
----------------------------------------------------------

Score of test data ----> 0.8981043915868532

---------------------------------------------------------

MSE of Model -------> 0.149356258

---------------------------------------------------------

RMSE of Model -------> 0.38646637369892867

---------------------------------------------------------

 R2 Score -----> 0.8981043915868532

------------------------------------------------------------
```

Here we use Lasso Regularization to avoid overfitting

In [37]:
```python
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[37]:
```
LassoCV(normalize=True)
```

In [38]:
```python
alpha = lassocv.alpha_
alpha
```

Out[38]:
```
0.00010200443251839897
```

In [39]:
```python
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[39]:
```
Lasso(alpha=0.00010200443251839897)
```

In [40]:
```python
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9999992584089135
```

Conclusion : Knn model has 99% score and there is no overfitting.

Decision Tree model instantiaing, training and evaluating

In [41]:
```python
DT = DecisionTreeRegressor()
DT.fit(x_train, y_train)
y_pred = DT.predict(x_test)
```

In [42]:
```python
print('----------------------------------------------------------\n')
print('Score of test data ---->', DT.score(x_test, y_test))
print('\n---------------------------------------------------------\n')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('\n---------------------------------------------------------\n')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('\n---------------------------------------------------------')
print('\n R2 Score ----->', r2_score(y_test, y_pred))
print('\n-------------------------------------------------------------')
```

```
----------------------------------------------------------

Score of test data ----> 0.9895797429767522

---------------------------------------------------------

MSE of Model -------> 0.015273774999999999

---------------------------------------------------------

RMSE of Model -------> 0.12358711502418038

---------------------------------------------------------

 R2 Score -----> 0.9895797429767522

-------------------------------------------------------------
```

Here we use Lasso Regularization to avoid overfitting

In [43]:
```
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[43]:
```
LassoCV(normalize=True)
```

In [44]:
```
alpha = lassocv.alpha_
alpha
```

Out[44]:
```
0.00010200443251839897
```

In [45]:
```
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[45]:
```
Lasso(alpha=0.00010200443251839897)
```

In [46]:
```
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9999992584089135
```

Conclusion : Decision Tree model has 99% score and there is no overfitting.

Random Forest model instantiaing, training and evaluating

In [47]:
```
Rn = RandomForestRegressor()
Rn.fit(x_train, y_train)
y_pred = Rn.predict(x_test)
```

In [48]:
```python
print('----------------------------------------------------------\n')
print('Score of test data ---->', Rn.score(x_test, y_test))
print('\n----------------------------------------------------------\n')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('\n----------------------------------------------------------\n')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('\n----------------------------------------------------------')
print('\n R2 Score ----->', r2_score(y_test, y_pred))
print('\n-------------------------------------------------------------')
```

```
----------------------------------------------------------

Score of test data ----> 0.9897123664218928

---------------------------------------------------------

MSE of Model -------> 0.015079378579999686

---------------------------------------------------------

RMSE of Model -------> 0.12279812123969848

---------------------------------------------------------

 R2 Score -----> 0.9897123664218928

------------------------------------------------------------
```

Here we use Lasso Regularization to avoid overfitting

In [49]:
```python
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[49]:
```
LassoCV(normalize=True)
```

In [50]:
```python
alpha = lassocv.alpha_
alpha
```

Out[50]:
```
0.00010200443251839897
```

In [51]:
```python
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[51]:
```
Lasso(alpha=0.00010200443251839897)
```

In [52]:
```python
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9999992584089135
```

Conclusion : Random Forest model has 99% score and there is no overfitting.

SVM model instantiaing, training and evaluating

In [53]:
```
svr = SVR()
svr.fit(x_train, y_train)
y_pred = svr.predict(x_test)
```

In [54]:
```
print('----------------------------------------------------------\n')
print('Score of test data ---->', svr.score(x_test, y_test))
print('\n----------------------------------------------------------\n')
print('MSE of Model ------->', mean_squared_error(y_test, y_pred))
print('\n----------------------------------------------------------\n')
print('RMSE of Model ------->', np.sqrt(mean_squared_error(y_test, y_pred)))
print('\n----------------------------------------------------------')
print('\n R2 Score ----->', r2_score(y_test, y_pred))
print('\n-------------------------------------------------------------')
```

```
----------------------------------------------------------

Score of test data ----> 0.9198940803614892

---------------------------------------------------------

MSE of Model -------> 0.11741742933950625

---------------------------------------------------------

RMSE of Model -------> 0.342662267166238

---------------------------------------------------------

 R2 Score -----> 0.9198940803614892

------------------------------------------------------------
```

Here we use Lasso Regularization to avoid overfitting

In [55]:
```
# LassoCV will return best alpha after max itratation.
# Normalize is subtracting the mean and dividing by the L2-norm.

lassocv = LassoCV(alphas = None, max_iter = 1000, normalize = True)
lassocv.fit(x_train,y_train)
```

Out[55]:
```
LassoCV(normalize=True)
```

In [56]:
```
alpha = lassocv.alpha_
alpha
```

Out[56]:
```
0.00010200443251839897
```

In [57]:
```
lasso_reg = Lasso(alpha)
lasso_reg.fit(x_train, y_train)
```

Out[57]:
```
Lasso(alpha=0.00010200443251839897)
```

In [58]:
```
print('Lasso Score =======>', lasso_reg.score(x_train, y_train))
```

```
Lasso Score =======> 0.9999992584089135
```

Conclusion : SVM model has 99% score and there is no overfitting.

Saving The Model

In [59]:
```
# saving the model to the Local file system
filename = 'finalized_Lr_model.pickle'
pickle.dump(Lr, open(filename, 'wb'))
```

Final Conclusion : Linear Regression is our best model.

In [ ]:
```
```