Type *Markdown* and LaTeX: α^2

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

In [2]:
```
#import dataset
df=pd.read_csv(r"E:\154\2015 - 2015.csv",low_memory=False).dropna(axis='column
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.
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0.
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0.
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0.
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0.
...	...	...	...	...	...	...	...	...	
153	Rwanda	Sub-Saharan Africa	154	3.465	0.03464	0.22208	0.77370	0.42864	0.
154	Benin	Sub-Saharan Africa	155	3.340	0.03656	0.28665	0.35386	0.31910	0.
155	Syria	Middle East and Northern Africa	156	3.006	0.05015	0.66320	0.47489	0.72193	0.
156	Burundi	Sub-Saharan Africa	157	2.905	0.08658	0.01530	0.41587	0.22396	0.
157	Togo	Sub-Saharan Africa	158	2.839	0.06727	0.20868	0.13995	0.28443	0.

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]:
```
#to display top 5 rows
df.head()
```

Out[4]:

	Country	Region	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freed
0	Switzerland	Western Europe	1	7.587	0.03411	1.39651	1.34951	0.94143	0.665
1	Iceland	Western Europe	2	7.561	0.04884	1.30232	1.40223	0.94784	0.628
2	Denmark	Western Europe	3	7.527	0.03328	1.32548	1.36058	0.87464	0.649
3	Norway	Western Europe	4	7.522	0.03880	1.45900	1.33095	0.88521	0.669
4	Canada	North America	5	7.427	0.03553	1.32629	1.32261	0.90563	0.632

Data cleaning and Pre-Processing

In [5]:
```
#To find null values
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 [6]:
```
# To display summary of statistics
df.describe()
```

Out[6]:

	Happiness Rank	Happiness Score	Standard Error	Economy (GDP per Capita)	Family	Health (Life Expectancy)	Freedom	(Gc C
count	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	158.000000	1
mean	79.493671	5.375734	0.047885	0.846137	0.991046	0.630259	0.428615	
std	45.754363	1.145010	0.017146	0.403121	0.272369	0.247078	0.150693	
min	1.000000	2.839000	0.018480	0.000000	0.000000	0.000000	0.000000	
25%	40.250000	4.526000	0.037268	0.545808	0.856823	0.439185	0.328330	
50%	79.500000	5.232500	0.043940	0.910245	1.029510	0.696705	0.435515	
75%	118.750000	6.243750	0.052300	1.158448	1.214405	0.811013	0.549092	
max	158.000000	7.587000	0.136930	1.690420	1.402230	1.025250	0.669730	

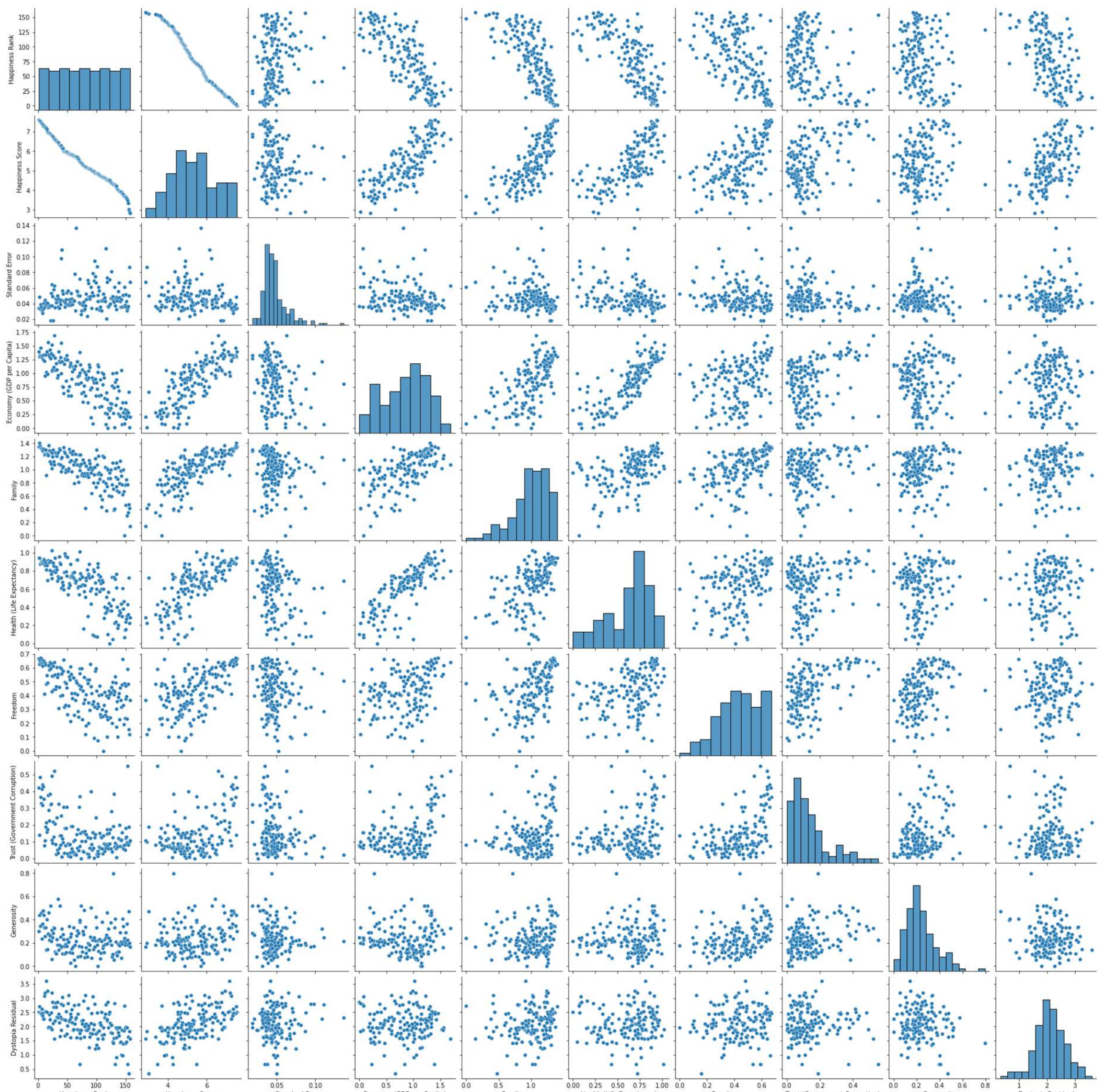
In [7]:
```
#To Display column heading
df.columns
```

Out[7]:
```
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')
```

EDA and VISUALIZATION

In [8]:
```
sns.pairplot(df)
```

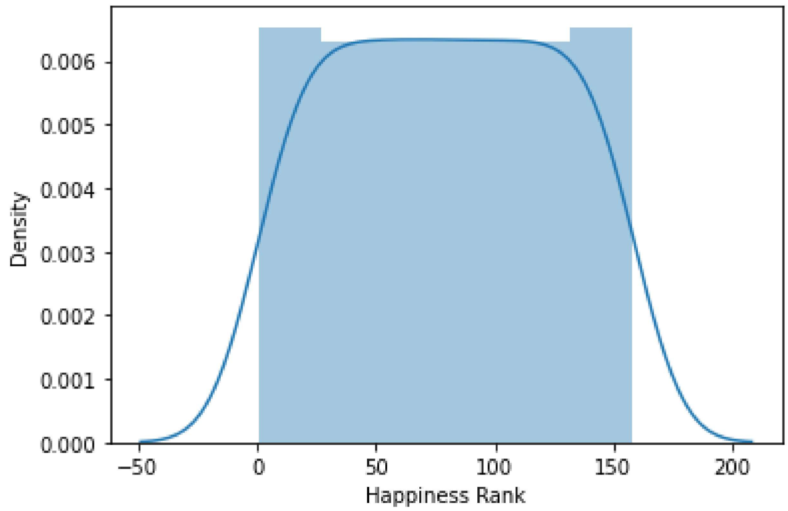
Out[8]: <seaborn.axisgrid.PairGrid at 0x16532709ac0>



In [9]:
```
sns.distplot(df['Happiness Rank'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[9]: <AxesSubplot:xlabel='Happiness Rank', ylabel='Density'>

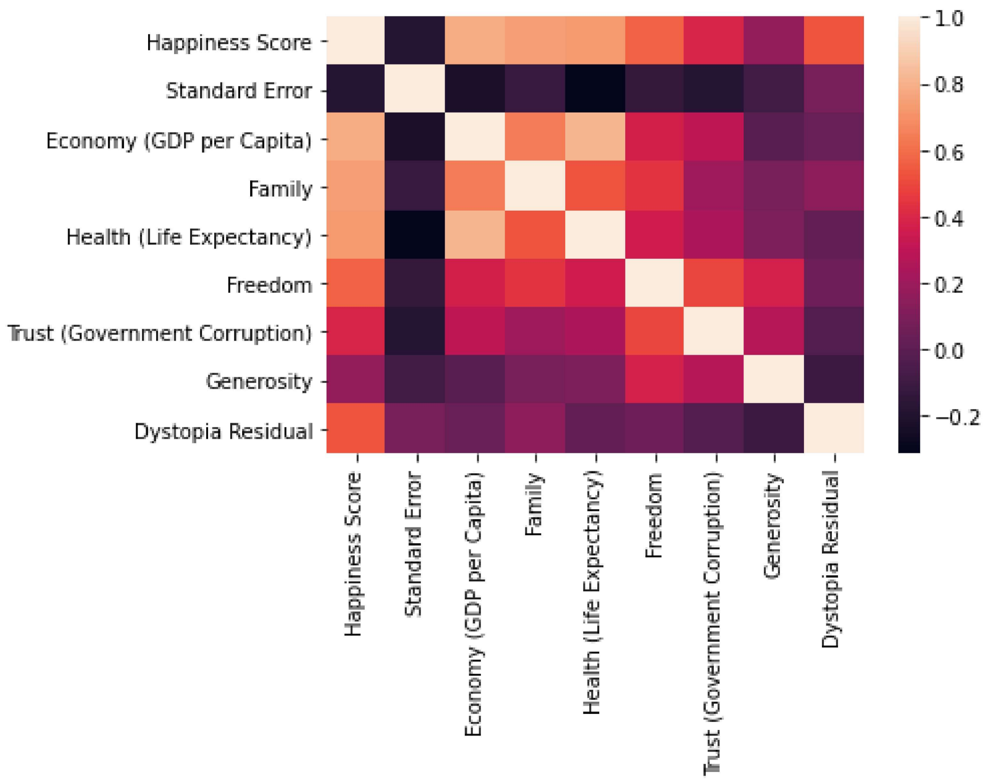


In [10]:
```
df1=df[['Country', 'Region', 'Happiness Score',
       'Standard Error', 'Economy (GDP per Capita)', 'Family',
       'Health (Life Expectancy)', 'Freedom', 'Trust (Government Corruption)',
       'Generosity', 'Dystopia Residual']]
```

Plot Using Heat Map

In [11]:
```
sns.heatmap(df1.corr())
```

Out[11]: <AxesSubplot:>



To Train The Model-Model Building

we are going to train Linera Regression Model;We need to split out data into two variables x and y where x is independent variable(input) and y is dependent on x(output) we could ignore address column as it required for our model

In [12]:
```
x=df1[['Happiness Score',
       'Standard Error', 'Economy (GDP per Capita)',
       'Health (Life Expectancy)', 'Freedom', 'Trust (Government Corruption)',
       'Generosity', 'Dystopia Residual']]
y=df1['Family']
```

To Split my dataset into training and test data

In [13]:
```

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 [14]:
```
from sklearn.linear_model import LinearRegression
lr= LinearRegression()
lr.fit(x_train,y_train)
```

Out[14]: LinearRegression()

In [15]:
```
lr.intercept_
```

Out[15]: -0.0001609872532650769

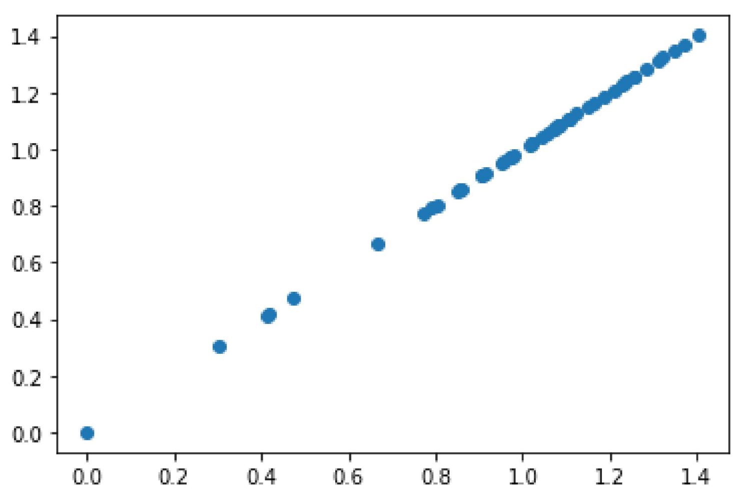
In [16]:
```
coeff = pd.DataFrame(lr.coef_,x.columns,columns=['Co-efficient'])
coeff
```

Out[16]:

	Co-efficient
Happiness Score	0.999970
Standard Error	-0.000543
Economy (GDP per Capita)	-1.000072
Health (Life Expectancy)	-0.999828
Freedom	-0.999520
Trust (Government Corruption)	-0.999829
Generosity	-1.000024
Dystopia Residual	-0.999954

In [17]:
```
prediction = lr.predict(x_test)
plt.scatter(y_test,prediction)
```

Out[17]: <matplotlib.collections.PathCollection at 0x165390f2be0>



Accuracy

In [18]:
```
lr.score(x_test,y_test)
```

Out[18]: 0.9999988920925807

In [19]:
```
lr.score(x_train,y_train)
```
Out[19]:
```
0.9999989896054637
```

In [20]:
```
from sklearn.linear_model import Ridge,Lasso
```

In [21]:
```
rr=Ridge(alpha=10)
rr.fit(x_train,y_train)
```
Out[21]:
```
Ridge(alpha=10)
```

In [22]:
```
rr.score(x_test,y_test)
```
Out[22]:
```
0.7009415594590706
```

In [23]:
```
la =Lasso(alpha=10)
la.fit(x_train,y_train)
```
Out[23]:
```
Lasso(alpha=10)
```

In [24]:
```
la.score(x_test,y_test)
```
Out[24]:
```
-1.3557709450662259e-05
```

ElasticNet

In [25]:
```
from sklearn.linear_model import ElasticNet
en = ElasticNet()
en.fit(x_train,y_train)
```
Out[25]:
```
ElasticNet()
```

In [26]:
```
print(en.coef_)
```
```
[ 0. -0.  0.  0.  0.  0.  0.  0.]
```

In [27]:
```
print(en.intercept_)
```
```
0.9907238181818183
```

In [28]:
```
print(en.predict(x_test))
```
```
[0.99072382 0.99072382 0.99072382 0.99072382 0.99072382 0.99072382
 0.99072382 0.99072382 0.99072382 0.99072382 0.99072382 0.99072382
 0.99072382 0.99072382 0.99072382 0.99072382 0.99072382 0.99072382
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 0.99072382 0.99072382 0.99072382 0.99072382 0.99072382 0.99072382]
```

In [29]:
```
print(en.score(x_test,y_test))
```

```
-1.3557709450662259e-05
```

Evaluation Metrics ¶

In [31]:
```
from sklearn import metrics
```

In [32]:
```
print("Mean Absolute Error",metrics.mean_absolute_error(y_test,prediction))
```

```
Mean Absolute Error 0.00026943036268065024
```

In [33]:
```
print("Mean Squared Error:",metrics.mean_squared_error(y_test,prediction))
```

```
Mean Squared Error: 9.187860411525314e-08
```

In [34]:
```
print("Root Mean Absolute Error:",np.sqrt(metrics.mean_squared_error(y_test,pr
```

```
Root Mean Absolute Error: 0.00030311483651456783
```

In [ ]:
```

```